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Equilibrium bidding in joint transmission and energy markets

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Equilibrium Bidding in Joint Transmission and Energy Markets

by

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DEDICATION

To my new born son Luis Can, my wife and family

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ABSTRACT

Participants in deregulated electric power markets compete for financial transmission rights (FTRs) to hedge against losses due to transmission congestion by submitting bids to the independent system operator (ISO). The ISO obtains an FTR allocation, that maximizes sales revenue while satisfying simultaneous feasibility. This FTR allocation remains in place for a length of time during which the participants compete in the energy market to maximize their total payoff from both FTR and energy markets. Energy markets (bi-lateral, day ahead, real time) continue until the the end of the current FTR period, at which time the participants can choose to modify their FTR holdings for the next FTR period. As in any noncooperative game, finding Nash equilibrium bidding strategies is of critical importance to the participants in both FTR and energy markets. In this research, a two-tier matrix game theoretic modeling approach is developed that can be used to obtain equilibrium bidding behavior of the participants in both FTR and energy markets considering the total payoff from FTR and energy. The matrix game model presents a significant deviation from the bilevel optimization approach commonly used to model FTR and energy allocation problems. A reinforcement learning (RL) algorithm is also developed which

uses a simulation model and a value maximization approach to obtain the equilibrium bidding strategies in each market. The model and the RL based solution approach allow consideration of multi-dimensional bids (for both FTR and energy markets), network contingencies, varying demands, and many participants.

The value iteration based RL algorithm obtains pure strategy Nash equilibrium for FTR and energy allocation. A sample network with three buses and four participants is considered for demonstrating the viability of the game theoretic model for FTR market. A PJM network example with five buses, five generators and three loads is also considered to analyze equilibrium bidding behavior in joint FTR and energy markets. Several numerical experiments on the sample networks are conducted using the approach of statistical design of experiments (DOE) to assess impacts of variations of bid and network parameters on the market outcomes like participant payoffs and equilibrium strategies.

CHAPTER 1

INTRODUCTION

Capacity limitations in the transmission grid constrain movement of power across the grid and thereby impose differential locational marginal prices (LMPs). This phenomenon, which may expose market participants to volatile energy prices is described as transmission congestion. Transmission congestion creates a dilemma for the system operator (ISO) as the revenues collected from the customers (retailers) exceed the payments to generators/suppliers. Electricity markets use instruments like financial transmission rights (FTRs) to hedge the market participants from the volatility of the congestion charges. This is accomplished through a redistribution of the excess revenue among the FTR holders (Hogan [1]).

Hence, FTR is a financial risk instrument intended to offset transmission users' congestion charges. An FTR is represented as MW amount between two points in the transmission network and is valid over a defined period of time. The definition of FTR also depends on how the transmission capacity (in MW) is specified and measured. FTRs defined between any two particular buses in the system are known as point-to-point financial transmission right (PTP-FTR). Holder of PTP-FTR is entitled to be paid if the difference in the locational marginal prices between the specified points of withdrawal and injection (ΔLMP)is positive. A much less common FTR type is referred to as flowgate financial transmission right (FGR-FTR), which grants the holder a capacity reservation or scheduling priority for using specific transmission links or flowgates. FGR-FTR between any two nodes can be obtained by combining the capacity reservations (FGRs) of the lines connecting the nodes. In this research, only PTP financial transmission rights are considered.

PTP-FTRs can be further classified as obligations or options depending on the financial settlement strategy. An FTR obligation is bi-directional and can have a negative or a positive price difference (ΔLMP). In case of a negative value of ΔLMP, the holder of the FTR makes a payment equal to the product of the FTR quantity times the ΔLMP. An FTR option is uni-directional and can only have a nonnegative value. That is, the holder of an FTR option is not expected to make a payment to the ISO if the ΔLMP is negative, but will be paid by the ISO when the ΔLMP is positive. In this research, a PTP-FTR bidder has a choice to bid for any combination of obligation and option.

After the PTP-FTR bids are submitted, two important conditions that are taken into account in allocating the available FTRs are:

1. Simultaneous feasibility
2. Revenue adequacy

Simultaneous feasibility refers to the condition where the allocated FTRs are within the capability of the existing transmission system. That is, tested by checking if the power flows that occur due to the allocated FTRs fall within the constraints of the system. Revenue adequacy is a condition whereby the net payments, collected by the system operator through the actual dispatch of energy, should be greater or equal to the payments made to the FTR holders. It has been shown that revenue adequacy follows from simultaneous feasibility [1].

It is considered that to acquire FTR on a path, market participants submit strategic bids to ISO comprised of four parameters: obligation price, option price, obligation quantity, and option quantity. FTR bidders are assumed to submit different bids for the FTR paths. Based on the bids, the FTRs are allocated such that ISO's revenue from FTR sales is maximized while satisfying the constraints of simultaneous feasibility condition. FTR bidders attempt to maximize their expected utility for holding an FTR. Two different approaches for obtaining equilibrium FTR bidding strategies are examined:

1. Considering bidding in the FTR market alone assuming that the estimates of ΔLMPs are available, and

2. Considering bidding in the FTR market in conjunction with bidding in the energy market to derive the actual LMPs.

The solution of joint FTR and energy markets is not found in the open literature.

In a deregulated electric power market with multiple bidders for FTRs, it is essential to understand the equilibrium bidding behavior and the resulting payoffs to the participants. It is also imperative to understand the impact of various network parameter values on the equilibrium outcome(s). A common approach adopted in the electric market literature to obtain equilibrium bidding behavior is a bi-level optimization method. This approach has also been used in the FTR market. In the bi-level method, the upper level problem obtains the equilibrium bids of the participants, while the lower level problem finds the corresponding FTR allocation via ISO's revenue maximization subject to the SFT constraints. The upper level problem attempts to find an equilibrium strategy by repeatedly updating bidders' strategies one at a time while assuming strategies of other bidders fixed until no further change in the strategies is possible. Such an approach can be found in a recent paper [2], which considers price as the only PTP-FTR bid parameter, and assumes that each bidder submits bid for a single FTR path. It is also assumed in the paper that the ΔLMP estimate is known to a bidder, and the bidder utility is a function of the risk coefficient and the variance of ΔLMP of the FTR path. Various methods that have been used to forecast LMPs are price simulation methods [3], statistical methods like artificial neural network method [3], [4], and time series method [5].

In this research, a matrix game theoretic approach to examining equilibrium FTR and energy bidding behavior of the participants in a deregulated power market is presented. The bids are considered to be a discrete valued vector of FTR prices and quantities. Also, a bidder is allowed to bid on any subset of the available FTR paths in a network. The matrix game theoretic model allows simultaneous solution of the equilibrium bidding behavior of the participants. A recently developed value iteration based reinforcement learning (RL) approach is used in solving for equilibrium FTR biding strategies [6]. A sample FTR network, that was studied in [2], is used in numerically demonstrating the matrix game theoretic modeling approach for FTR allocation under ΔLMP assumptions. A PJM-5 bus example is used to study the joint FTR and energy allocation process. Experiments are conducted to determine the impacts of the bid and network parameters through single factor analysis and multi-factor analysis using factorial experimental design and consequent analysis of variance.

This dissertation is organized as follows. Chapter 2 provides the literature about the transmission rights in deregulated electric market. Chapter 3 presents the formulations to model the FTR allocation problem as a matrix game and value iteration based RL algorithm to solve the equilibrium bidding strategies. Chapter 4 presents the formulations to integrate the FTR and energy markets and find the equilibrium strategies with this joint model. Chapter 5 presents the numerical experiments and their results when FTR allocations are done using estimation of ΔLMPs. Chapter 6 provides the numerical experiments with results to reveal the significant factors when the FTR and energy markets are settled jointly. Conclusions are summarized in Chapter 7.

CHAPTER 2

LITERATURE REVIEW

The move towards a deregulated electric power industry has raised the awareness of the critical impact of transmission congestion on power networks. Limitations in the transmission grid constrain long-distance movement of power, which results in higher prices in certain locations of the network. This phenomenon is termed as transmission congestion, and the difference in the locational marginal prices (LMPs) between any two busses is called congestion cost (transmission charge) to the participants at those busses. Electricity markets use various transmission right mechanisms to hedge the market participants from the volatility of the transmission charges. Transmission rights allow their holders to derive benefits from the use of the transmission capacity as follows:

1. Financial benefits resulting from the use of the capacity

2. Right to use the transmission capacity.

Hence, the transmission rights could be financial and/or physical in nature. A purely financial approach, known as financial transmission rights (FTR), provide market traders and other market participants an instrument for constructing financial hedges. The Federal Energy Regulatory Commission (FERC), in a notice of public ruling (NOPR) in 2002, proposed location-based marginal pricing together with FTRs as the mechanism to build efficient energy markets ([7]). The above ruling, according to Hogan [8], sets the right incentives to the market participants. LMP-based FTR markets have been in operation in New York and PJM for a few years. New England has recently adopted this, while the Midwest and California markets are scheduled to implement this structure soon [9]. The above markets together represent a significant portion of United State's electricity market.

2.1 FTR: Financial Transmission Rights

Transmission congestion creates a dilemma for the system operator as the revenues collected from the customers exceed the payments to generators. The additional revenue is referred to as the congestion revenue. Hogan [10] suggests that a convenient solution to this dilemma would be to re-distribute the congestion revenue through a system of long-run financial transmission rights (FTRs). FTR is defined as a financial risk instrument intended to offset the congestion charges incurred in a transmission network. FTR serves to not only protect a market participant from the losses linked with congestion but also as a means of generating revenue in a deregulated market, in a way similar to the stocks in the financial sector. It is also referred to in the literature as transmission congestion contract (TCC) or congestion revenue right (CRR). Various types of existing FTR contracts are discussed below.

2.1.1 Point-to-Point FTR and Flowgate FTR

The definition of FTR further depends on how the transmission capacity is specified. FTR between any two particular buses in a system is known as point-to-point (PTP) financial transmission right, which is also called firm transmission right or just FTR. Owner of PTP FTR is entitled to be paid if the difference in the locational prices between the specified point of withdrawal and injection is positive. The other less frequently used FTR type is the flowgate (referred to as FGR). In a constrained dispatch, a flowgate has a shadow price, which defines the flowgate's market clearing price. Flowgate FTR is a contract to collect the shadow price from the realized dispatch for a specified quantity of the constraint. This approach creates the idea of selling the line limits or resources besides the electric flow on the lines TrHoganF02.

Generators and loads are interested in being able to transfer power between two specific locations in the network. O'neill et. al [11] state that PTP FTRs are well suited for hedging congestion cost for such cases in the long run. However, existence of a large number of possible PTP combinations makes it difficult to choose in the dynamic environment of electric trade. As a result, resellers of PTP contracts face a thin market. Furthermore, any change in configuration of PTP rights require simultaneous feasibility which has to be solved by the regional transmission operator (RTO) with all other rights. This centralized optimization procedure limits the development of off-RTO secondary markets for PTP rights [12]. Adamson [13] presents a new method of trading PTP transmission rights which is claimed to decrease the level of central optimization. This method is based on the principles of unequal exchange rates between different point-to-point transmission rights.

Though FERC has recently endorsed the merit of having flowgate transmission rights, there is a lot of debate surrounding the subject. Chao et al. [14] propose flow-based systems as a potentially efficient method of trading rights that does not require centralized optimization. Moreover, electricity traders often argue that since there will be fewer congested flowgates compared to number of node combinations in PTP rights, flow-based rights will yield a more liquid forward market for energy and transmission. However, the number of transmission rights that must be defined to account for all of the actual or possible constraints on an actual network may be large and impractical [15]. Andrew [16] suggests that FGR systems when implemented in large grids may not capture all the congestion costs in the system, forcing the operator to provide continuous update of the new commercially significant flowgates.

2.1.2 Types of FTR: Options and Obligations

Financial transmission rights can be defined as obligations or options depending on the financial treatment to the holder of the right.

Obligation: An FTR obligation is bi-directional and can have a negative value or a positive value. In case of a negative value the holder of the FTR makes a payment equal to the product of the FTR quantity times the price difference. A similar payment is received by the holder, from the ISO, if the FTR has a positive value. This type of FTR is commonly used due to its ease of implementation though it is not as practical from an economic standpoint.

Option: An FTR option is uni-directional and can only have a positive value. That is, the holder of the FTR is not expected to make a payment to the ISO if the FTR is negative but will always be paid by the ISO when the FTR is positive. It is natural that this type of FTR would be more appealing to market participants however an FTR option tends to cost more at auction than its equivalent obligation. Moreover, practical implementation of this type of FTR is a complex task. For example, in a power network of 3000 buses, there would be upwards of 100,000 constraints. Solving for an FTR option would require evaluation of each of these individual constraints, a task which is daunting.

An FTR auction for both point-to-point obligations and options is similar to an economic dispatch problem [1]. But in FTR auction for options, evaluating a contingency and constraint condition requires solving an unconstrained optimal power flow for the worst-case impact. This increases the complexity of the model and hence success with this auction model has not yet been demonstrated. In the case of NYISO working with an AC (Alternating Current) power network further complicates its efforts at implementing FTR options. On the other hand, an FTR auction for flowgate obligations or options is more complicated and it is not like an economic dispatch problem. In this model, there could be a large number of flowgates in the real grid that greatly complicates any construction of hedges. Also the required flowgate amounts to hedge any transaction change frequently with changing dispatch restrictions. A hybrid model with point-to-point and flowgate obligations and options can produce a computational challenge and it is not clear whether this auction model could be solved for a realistic grid. O'neill et al. [11] propose an auction-based process that allows the market participants to acquire and reconfigure the financial transmission rights. The paper shows that by allowing flowgate and point-to-point obligations and options to be reconfigured and exchanged, the market can decide what combination of financial rights are most useful to the market participants.

2.1.3 Simultaneous Feasibility and Revenue Adequacy

Two important aspects, which are considered to assess viability of the FTRs are simultaneous feasibility and revenue adequacy. In electric power networks, conditions such as thermal limits, power limits, generating capacity, and demand vary with time. As a result, FTR allocation may need to be varied to maintain electrical and economic constraints. These constraints are known as simultaneous feasibility and revenue adequacy. Simultaneous feasibility refers to testing whether the allocated FTRs are within the capability of the existing transmission system. That is, the power flows that occur due to the allocated FTR must fall within the constraints of the system. Revenue adequacy is a condition whereby the net payments, collected by the system operator through the actual dispatch of energy, should be greater than the payments to the FTR holders. The ISO constantly checks for the viability of these allocated FTRs by performing a simultaneous feasibility test (SFT).

The SFT is done by modeling the FTRs as generation at point of injection (source point) and load at point of withdrawal (sink point). An AC power-flow analysis is carried out to evaluate if the system will remain within all permissible limits, including single contingency situations (like the loss of a line etc.). This power flow analysis employs an optimization program that is used to simulate the working of the actual power network. This program is called the economic dispatch program or optimal power flow. Once the parameters of the power network have been modeled into the program, it simulates the actual operation of the network under varying conditions and parameters. If the outstanding FTR violate any of the system limits then they are considered to be unviable. This will usually result in the ISO running the allocation program again to obtain a re-allocation or in the worst case asking the market participants to bid again. The allocated FTR must also ensure that the excess revenue (congestion charges) collected by the ISO is adequate to cover the payments required under the FTRs. Fortunately however, both of the above conditions need not be individually verified. It has been proven that revenue adequacy follows from simultaneously feasibility [1].

2.2 Settlement Approaches in FTR Market

Ideally, an optimal security constrained dispatch is the dispatch that gives similar results like the unconstrained dispatch with equal LMPs at all system buses. However, constrained transmission considerably impacts energy prices as indicated by large fluctuations in LMPs. This forces participants to play strategically with the market tools like auctions and FTRs. In the end, the system settles down by solving a social-welfare problem. In [2], Li and Shahidehpour formulate FTR auction problem as a linear program with the objective of maximizing the revenue collected from the FTR auction market. An FTR bidder's objective is to maximize its expected utility for holding an FTR.

2.2.1 Bidding Strategies

The auction is the central mechanism of an FTR market. To buy or sell FTR, market participants submit quantity, cost information and points of injection and delivery in the form of bids, to the ISO. The ISO being the neutral party arbiter runs an FTR auction to allocate the FTRs. The bids are allocated such that they maximize the revenue from FTR sales while satisfying the simultaneous feasibility condition. As a result, user's bidding behaviors become significant. Bidders make their decisions based on anticipated system operating conditions while holding FTRs. Specifically, they need to estimate LMP differences between sink and source points on a certain FTR path and identify potential competitors and their corresponding bidding information [2]. The methods that forecast the electricity price include price simulation methods [3], statistical method such as artificial neural network [3], [4], and time series [5]. Each FTR bidder's objective is to maximize its expected utility for holding an FTR. Understanding this behavior is a work in progress. The problem is to determine the competitive equilibrium bidding strategies in an FTR auction by considering the equilibrium profits realized in the energy market as the performance measure. A sound bidding strategy is needed for purchasing FTRs, for the following reasons. If the bid price is too low, sufficient FTRs may not be allocated resulting in the supplier paying high congestion costs. On the other hand, bidding too high will likely win ownership of the auctioned FTR, but may mean loss of profit. Market participants in their efforts to bid for FTRs should take into account two important factors. One of these factors is the estimated price differential between the supply node and the load node, for which an accurate prediction of future locational prices is important. The other factor is the anticipated total supply quantity as it ideally represents the amount of power that needs to be hedged against the congestion costs. Li and Shahidehpour [2] model the FTR bidding problem as a bilevel optimization with the upper subproblem representing bidders and the lower subproblem representing the solution to the ISO's FTR market clearing problem. Their results presented bidding differences between FTR obligations and options. Furthermore, the results showed that forecasting an accurate LMP differences and proper risk preferences were the critical points in FTR bidding and bidders' payoffs.

2.2.2 FTR Auctions

An auction is defined as the method of allocating goods under competition. Auctions are essentially pricing mechanisms. Increasingly, in a deregulated power market environment, market participants who may or may not have the ability to actually schedule power supply in the network, are attempting to buy and sell FTR in order to profit from the revenues and payments warranted under the FTR system. As the number of participants increases, the competition to buy or sell FTRs also increases. This rising trend in competition has ensured that at any time there are numerous participants vying for the same FTR. Such a situation fosters the need to utilize well-established methods of selling or buying FTR to multiple market participants, while increasing the revenue generated for the ISO. Worldwide, a variety of auction strategies are utilized in many market scenarios to carry out trading on similar grounds. Ideally, the FTR auction mechanism should increase price certainty of the energy market and improve market efficiency in the long run. The choice of an auction mechanism affects the prices in the market. It is hence worthwhile to investigate the various auction rules and strategies.

Auctions used in electricity markets are called multi-unit auctions since more than one unit of the same type is auctioned. Two forms of multi-unit electricity auctions are commonly used in present day restructured electricity markets: uniform price auction and discriminatory auction. The uniform price auction is further differentiated as first price uniform auction and second price uniform auction. A review of the literature suggests that different auction rules have not been compared for their effectiveness in trading FTR.

The initial and most important requirement to test various auction rules on the selling and buying of FTR is a computational framework able to evaluate the effects of different auction strategies on FTR allocation. That is, a means of allocating the FTR is required in which an auction framework can be embedded. Commonly practiced methods of FTR allocation use DC (Direct Current) approximations to an AC network scenario to determine load flows and guarantee simultaneous feasibility and revenue adequacy. In recent years, system operators have begun using non-linear optimization algorithms that model an AC network without any approximations. The optimal power flow (OPF) is a popular algorithm that is utilized for this purpose.

2.2.3 Optimal Power Flow

OPF is a generic term that describes a broad class of problems which try to optimize a specific objective function while satisfying constraints dictated by the operational and physical characteristics of the electric network [17]. The OPF algorithm is concerned with the physical allocation of generation capacities and the objective function is generally to minimize cost of supplying power. It is therefore necessary to transform its structure to make it suitable for FTR allocation as suggested by Hogan [1].

OPF is involved in the solution of a large-scale non-linear mathematical programming problem and it has taken mathematicians and scientists many decades of research to develop efficient algorithms to solve it. The unique feature of OPF is that the cost of operating the network can be minimized while maintaining the functional constraints. Significant progress has been achieved in this area [18], [19], [20]. Many optimization techniques have been employed to solve the OPF problem. The techniques are classified as follows [17]:

1. Non linear programming
2. Quadratic programming
3. Newton based solutions of optimality conditions
4. Linear programming
5. Hybrid versions of LP and IP
6. Interior point methods

The deregulated power market has increased the need for fast reliable and accurate OPFs capable of simulating the real time spot market. Variations occurring in real time have to be modeled with greater accuracy. Recent years have seen the focus shifting to adapting the formulation of OPF to work in a deregulated power market environment [21], [22], [23], [24], [25]. Increase in computational capabilities and improved mathematical algorithms have ensured that OPF is robust enough to be employed in a deregulated environment. The rise in the use of the World Wide Web (due to increase in bandwidth and data transfer capabilities) [22] brought the optimal power flow to the forefront of real time, online multiple participant interaction simulations of the deregulated market. In [21], Yong and Lassater take into account the presence of multiple market participants who have the ability to select their own energy supplier.

The formulation for OPF can be categorized based on the type of power network: alternating current optimal power flow (AC-OPF) and direct current optimal power flow (DC-OPF). In the literature, DC-OPF is widely used to formulate the OPF problem in AC networks, since DC-OPF is faster compared to the AC-OPF. The DC-OPF formulation is obtained by ignoring reactive power balance equations, line losses and tap dependence in transformer reactance and assuming that all voltage magnitudes are identically one per unit. The DC-OPF hence converts the power flow problem to a linear problem and solves a linear set of equations. The disadvantage of DC-OPF is that all non-linear system parameters are converted to linear form thereby compromising on the ability of the optimization program to accurately model the system.

The formulation for AC-OPF is complex and non linear in nature. This complexity though, is offset by the benefits that it offers. The major benefit of AC-OPF is that it internalizes losses, i.e., during the economic dispatch process the supply generators are set at a higher level to compensate for both the actual load and the losses that occur from the dispatch for that load. The LMPs that result from this dispatch will reflect the cost of generation to compensate for these losses. It also models reactive power and voltage constraints in the system making the AC-OPF dispatch a much more accurate and realistic representation of the power system. As a result the AC-OPF provides us with a comprehensive framework for the FTR auction process.

2.2.4 Performance Measures

Electric dispatch problem can have different solutions. Which dispatch alternative is optimal depends on the performance measures. In [26], Alomoush introduces some performance indices to quantify severity of congestion, degree of system utilization and uniformity of energy prices. Total congestion charge, total system generation, index of total generation charge, index of locational marginal prices, average locational marginal price of generation/load and system utilization are the indices that the author proposes. Based on these indices different dispatch scenarios can be compared and optimal dispatch can be determined. Some indices will be more important than the others depending on the performance priorities. Power system stability is another performance measure that has to be taken into consideration while choosing the appropriate dispatch scenario. Some dispatches may yield more preferred outcomes; however, it may create a less secure power system. Power systems with very close to the voltage collapse point, which can be measured by an appropriate steady-state voltage stability indicator [27], [28], should be avoided.

2.2.5 FTR Market Power

In FTR markets, it is important to monitor situations in which holders can increase their FTR payouts by increasing the relevant congestion intentionally. Because of particular characteristics of power markets, it is possible to exercise market power as in no other kind of market. In [29], [30], [31], strategic behavior of FTR holders has been analyzed in a two-node network. It has been shown that if a generator in the importing node holds an FTR, it increases its power market; however, if the FTR is held by a generator in the exporting node, it has no effect in the market power of the generator. Oren [32] argues that centralized implementation of FTRs will result in inefficient dispatch and market power for the generators. Stoft [29] provides a counter-argument to Oren's conclusion and proves that under certain "excess capacity" conditions, financial transmission rights curb market power. Joskow et al. [33], [34] study the impact of allocation of financial and physical transmission rights on market power. [33], [34], [35] conclude that the effect of rights depend upon numerous factors including the configuration of the underlying market power problems (location of buyer and seller) and the microstructure of the market for transmission rights. In [36], Bautista and Quintana propose a method based on relative hedging position ratios to screen and discriminate FTRs with market power potential.

CHAPTER 3

A MATRIX GAME MODEL FOR SETTLEMENT OF FTR MARKET

3.1 A Matrix Game Model Formulation for FTR Allocation

Let $\mathcal{I} = \{1, 2, \cdots, I\}$ denote the set of paths of source and sink locations for which FTRs can be obtained. Also, let $\mathcal{N} = \{1, 2, \cdots, N\}$ denote the set of participants bidding for the available FTRs. A bidder $n \in \mathcal{N}$ is considered to bid on a subset of paths $\mathcal{I}_n \subset \mathcal{I}$ with a 4-dimensional bid vector for each path consisting of price (as a fraction of the ΔLMP estimate for both obligation and option), quantity (as a fraction of the maximum flow limits), and FTR type mix factor (indicating proportion of the quantity that is categorized as obligation, and the rest of the quantity as option). A bid vector for bidder n for path $i \in \mathcal{I}_n$ can be denoted as

$$a_i^n = \left(k_i^{n,ob} \Delta LMP_i^n;\ k_i^{n,op} \Delta LMP_i^n;\ l_i^n Q_i;\ m_i^n \right),$$

where

$k_i^{n,ob}$	n^{th} bidder's obligation price bid factor valued between 0 and 1,
$k_i^{n,op}$	n^{th} bidder's option price bid factor valued between 0 and 1,
ΔLMP_i^n	n^{th} bidder's forecast of cumulative LMP difference between sink and source buses of path i over all FTR holding periods P (i.e., $\Delta LMP_i^n = \sum_{p=1}^{P} \Delta LMP_{i,p}^n$).
l_i^n	n^{th} bidder's quantity bid factor valued between 0 and 1,
Q_i	approximate maximum flow of electricity on path i, and
m_i^n	n^{th} bidder's bid for FTR type mix factor valued between 0 and 1 on path i, where: 0 indicates all FTR quantity bid as options, and 0.5 indicates equal division of FTR quantity between options and obligations.

The bid vector of participant n can be given as $a^n = (a_i^n;\ \forall i \in \mathcal{I}_n)$. Then the complete bid vector of all the players can be denoted as $\mathbf{a} = (a^1, a^2, \cdots, a^N)$. Since $|\mathcal{I}_n|$ denotes the number of paths on which bids are submitted by bidder n, the dimension of the bid vector for the bidder n is $4 \times |\mathcal{I}_n|$. Since the N bidders are in competition to maximize their FTR benefits, the non-cooperative bidding process can be modeled as an N-player matrix game, if the continuous bid vector elements are suitably discretized. A higher level of discretization gives better approximation to the real scenario, though at a higher cost of computation. If, for example, the bid vector elements $k_i^{n,ob}$, $k_i^{n,op}$, l_i^n, and m_i^n are discretized at eleven levels each (starting at 0 with 0.1 increments up to 1), then the action space of bidder n can be given as $(11 \times 11 \times 11 \times 11)^{|\mathcal{I}_n|}$. Hence, the matrix game consists of N payoff matrices each of size $(11 \times 11 \times 11 \times 11)^{|\mathcal{I}_1|} \times (11 \times 11 \times 11 \times 11)^{|\mathcal{I}_2|} \times \cdots \times (11 \times 11 \times 11 \times 11)^{|\mathcal{I}_N|}$.

Formulation of a matrix game would require computation of the payoff matrix elements. These elements represent utilities of the bidders obtained from a detailed consideration of variance and risk associated with ΔLMP estimates, network constraints and contingencies, and ISO's settlement. In what follows, the details for computing the elements of the payoff matrices are provided.

3.1.1 Computation of Payoff Matrix Elements

For any given bid combination, the ISO's revenue maximization model is solved first to determine the FTR allocations for the bidders for each path included in their bids. The FTR quantities are then used to calculate revenues for the players, which are then converted to utility values considering the variabilities in the ΔLMP estimates of the players and their risk coefficients.

3.1.1.1 ISO's FTR Revenue Maximization Model

A dc model is adopted for FTR allocation. Adaptation of the dc model is solely for simplification of the computational needs of this research. A true ac model can be substituted for real life implementations requiring higher computing power. The optimization model maximizes ISO's revenue from FTR allocations while considering simultaneous feasibility for the network. The model can be given as follows.

$$max \sum_{n=1}^{N} \sum_{i \in \mathcal{I}_n} \rho_i^{n,ob} * FTR_i^{n,ob} + \rho_i^{n,op} * FTR_i^{n,op} \tag{3.1}$$

s.t.

$$\sum_{n=1}^{N} \sum_{i \in \mathcal{I}_n} [D_{i,l}^{n,c} * FTR_i^{n,ob} + max(0, D_{i,l}^{n,c}) * FTR_i^{n,op}] \le B_l^c \quad \forall\, l,\ c \tag{3.2}$$

$$\sum_{n=1}^{N}\sum_{i\in\mathcal{I}_n}[-D_{i,l}^{n,c} * FTR_i^{n,ob} + max(0,-D_{i,l}^{n,c}) * FTR_i^{n,op}] \leq B_l^c \quad \forall\, l,\ c \tag{3.3}$$

$$FTR_i^{n,ob} \leq m_i^n * Q_i^n \quad \forall\, n,\ i \tag{3.4}$$

$$FTR_i^{n,op} \leq (1-m_i^n) * Q_i^n \quad \forall\, n,\ i \tag{3.5}$$

where

$FTR_i^{n,ob}$	quantity of obligation FTR allocated to n^{th} bidder on path i (decision variable)
$FTR_i^{n,op}$	quantity of option FTR allocated to n^{th} bidder on path i (decision variable)
$\rho_i^{n,ob}$	obligation bid price of n^{th} bidder on path i
$\rho_i^{n,op}$	option bid price of n^{th} bidder on path i
$D_{i,l}^{n,c}$	PTDF of the n^{th} bidder's i^{th} path on line l under contingency c
B_l^c	capacity limit of line l under contingency c
Q_i^n	upper bidding quantity of bidder n for path i (i.e., $Q_i * l_i^n$)

The relationship between a transaction (power injection at one bus to be withdrawn at another bus) and how much of that transmission flow on a line is called the power transfer distribution factor (PTDF). PTDFs can be used in ISO's FTR settlement model to check the line limits. That is, line capacities become resources in FTR settlement model. When the shadow prices are added over all lines, marginal clearing price for an FTR is found.

3.1.1.2 Expected FTR Revenue of a Bidder

Based on ISO's FTR allocation, the expected revenue for bidder n, R^n, can be obtained as follows:

$$R^n = \sum_{i \in \mathcal{I}_n} [\Delta LMP_i^n * FTR_i^{n,ob} + max(\Delta LMP_i^n, 0) * FTR_i^{n,op} - (MCP_i^{n,ob} * FTR_i^{n,ob} + MCP_i^{n,op} * FTR_i^{n,op})] \tag{3.6}$$

where

R^n	n^{th} bidder's expected revenue
$MCP_i^{n,ob}$	market clearing price for obligation FTR of bidder n in path i
$MCP_i^{n,op}$	market clearing price for option FTR of bidder n in path i

R^n shows the expected revenue ($) over all paths that the participant n has submitted bids for (This is a peculiar situation since the participant can play with the bids on the paths that he is bidding. At the same time, participant competes both with his rivals and himself to maximize the total FTR revenue). Discriminatory price auction is used for the ISO's FTR settlement model. As a result, $MCP_i^{n,ob}$ and $MCP_i^{n,op}$ are simply bidder n's obligation and option price bid respectively for path i. That is, marginal clearing price for an FTR path is determined by the winning bidder.

3.1.1.3 FTR Utility of a Bidder

Revenues for the bidders are calculated at the energy market with the actual ΔLMPs. However, since the nodal energy prices are volatile, a mean value and a variance are considered by the bidders for each ΔLMP estimate. To hedge against the variability of ΔLMPs, the bidders consider a risk factor in computation of their actual payoff (utility) as follows ([2]):

$$U^n = R^n \, - \, r^n * var\,(R^n)\,, \tag{3.7}$$

where

U^n	utility of bidder n,
r^n	risk coefficient of bidder n, and
$var(R^n)$	variance of bidder n's revenue estimate.

The level of risk depends on the bidder behavior (neutral, risk-averse, or risk-taker), which is captured by the sign and magnitude of r value. Bidders are chosen to be risk averse in this study. The variance can be obtained from the covariance estimates of the $\Delta LMPs$ as shown in [2]. In the following section, an algorithm is presented that can be used to obtain a Nash equilibrium FTR bidding strategy for the bidders.

3.2 Solution of Matrix Game for Equilibrium FTR Bidding Strategy

In this section a recently developed approach is discussed to obtain Nash equilibrium of N-player matrix games ([6]). Let $V^n(\mathbf{a})$ denote the payoff matrix of the n^{th} player of which $r^n(a^1, \cdots, a^N)$ are the matrix elements. Define the value of an action a^n to player n as

$$V^n(a^n) = \sum_{\{a^1,\cdots,a^N \setminus a^n\}} p(a^n, a^{-n}) r^n(a^1, \cdots, a^n, \cdots, a^N), \tag{3.8}$$

where: $p(a^n, a^{-n})$ denotes the probability of choice of an action combination a^{-n} by all the other players while player n chose action a^n. In decision making problems with a single player (those are modeled as MDPs and SMDPs), there exist optimal *values* for each state-action pair, and the highest *value* determines the optimal action in each state ([37]). Drawing an analogy from MDPs, for matrix games that have multiple players and a single state, it is conjectured that there exist optimal *values* over all actions of the players that can yield pure NE strategies. However, the probabilities ($p(a^n, a^{-n})$) needed to compute these *values* are impossible to obtain for real life problems without prior knowledge of bidders' behavior. Therefore, a learning approach is employed to estimate the *values* of the actions as follows. (3.8) is rewritten as

$$V_{t+1}^n(a^n) = (1-\gamma_t)\left[V_t^n(a^n)\right] \; + \gamma_t \; \left[r^n(a^1, \cdots, a^n, \cdots, a^N)\right], \tag{3.9}$$

where: t denotes the iteration count. The algorithm presented below utilizes the value learning scheme (3.9) to derive pure NE strategies for N-player matrix games.

3.2.1 A Value Iteration Algorithm for N-Player Matrix Games

It is assumed that the game has N-players and each player n has a set of A^n possible actions to choose from. Hence, N different reward matrices of size $|A^1| \times |A^2| \times \cdots \times |A^N|$ are available.

The Algorithm:

1. Eliminate rows and columns of the matrices associated with the dominated actions. A dominated action is one that will never be adopted by a rational player irrespective of the choices of other players. An action $a^n \in A^n$ for player n is said to be dominated if $r^n(a^n, a^{-n}) \leq r^n(\hat{a}^n, a^{-n})$, where: $\hat{a}^n \in A^n \backslash a^n$ and a^{-n} denotes the actions of all other players.

2. Let iteration count $t = 0$. Initialize the *values* for all actions of the player $V^n(a^n)$ to zero. Also initialize the learning parameter γ_0, exploration parameter

ϕ_0, and parameters γ_τ, ϕ_τ needed to obtain suitable decay rates of learning and exploration, respectively. Let *Maxsteps* denote the maximum iteration count.

3. If $t \leq$ *Maxsteps*, continue learning of the *values* through the following steps.

   (a) Action Selection:

   Greedy action selection for pure strategy Nash equilibrium:

   Each player n, with probability $(1 - \phi_t)$, chooses a greedy action $\hat{a}^n$ for which $V^n(\hat{a}^n) \geq V^n(a), \forall a \in A^n \backslash \hat{a}^n$. A tie is broken arbitrarily. With probability ϕ_t, the player chooses an exploratory action from the remaining elements of A^n (excluding the greedy action), where each exploratory action is chosen with equal probability.

   (b) *Value* Updating: Update the specific *values* for each player n corresponding to the chosen action a^n using the learning scheme given below.

$$V^n_{t+1}(a^n) \leftarrow (1 - \gamma_t) V^n_t(a^n) + \gamma_t \left(r^n(a^n, a^{-n}) \right). \tag{3.10}$$

   (c) Set $t \leftarrow t + 1$.

   (d) Update the learning parameters γ_t and exploration parameter ϕ_t following the DCM scheme given below ([38]):

$$\Theta_t = \left(\frac{\Theta_0}{1 + u} \right), \quad \text{where} \quad u = \left(\frac{t^2}{\Theta_\tau + t} \right), \tag{3.11}$$

   where: Θ_0 denotes the initial value of a learning/exploration rate, and Θ_τ is a large value (e.g., 10^9) chosen to obtain a suitable decay rate for the learning/exploration parameters. Exploration rate generally has a large starting value (e.g., 0.8) and a quicker decay, whereas learning rate has a small starting value (e.g., 0.1) and very slow decay rate. Exact choice of these values depends on the application ([38, 39]).

(e) If $t < MaxSteps$, go to Step 3(a), else go to Step 4.

4. Equilibrium Strategy Determination: From the final set of *values*, obtain the equilibrium strategy as follows.

   Pure strategy equilibrium: For each player n, the pure strategy action is a^n for which $V^n(a^n) = \max_{a \in A^n}\{V^n(a)\}$. The pure actions of all players combined constitute the pure strategy equilibrium.

CHAPTER 4

JOINT FTR AND ENERGY BIDDING MODEL

There have been many studies in literature about either the FTR market or the energy market, however, there is only a limited number of studies that examine the both markets together ([11] is one example). FTR and energy markets affect each other directly, in fact, revenues for holding an FTR is determined at energy market and one of the main motivation of having an FTR is to hedge against the volatile energy market LMPs. Therefore, integrating these two markets will not only reflect the real life scenario but also make it possible to analyze different aspects of the joint market that would be based on assumptions otherwise. Such a joint model can be used to investigate the effects of FTRs on participants' bidding strategies in energy market. Effects of dynamic environment of the energy market such as varying contingency and demand scenarios on the equilibrium settlements can also be studied through such an approach. Market power due to FTRs, effects of suppliers' generation cost functions are some other topics that can be analyzed with a joint model. In short, an integrated model of both FTR and energy markets is a more realistic representation of real life scenario and will allow a more detailed analysis about the power market.

A joint transmission and energy market implementation in real life is given in Figure 4.1. As seen from the figure, first participants compete for FTRs. After ISO clears the FTR market, participants hold the allocated FTRs until the end of FTR auction horizon during which energy market settlements take place regularly.

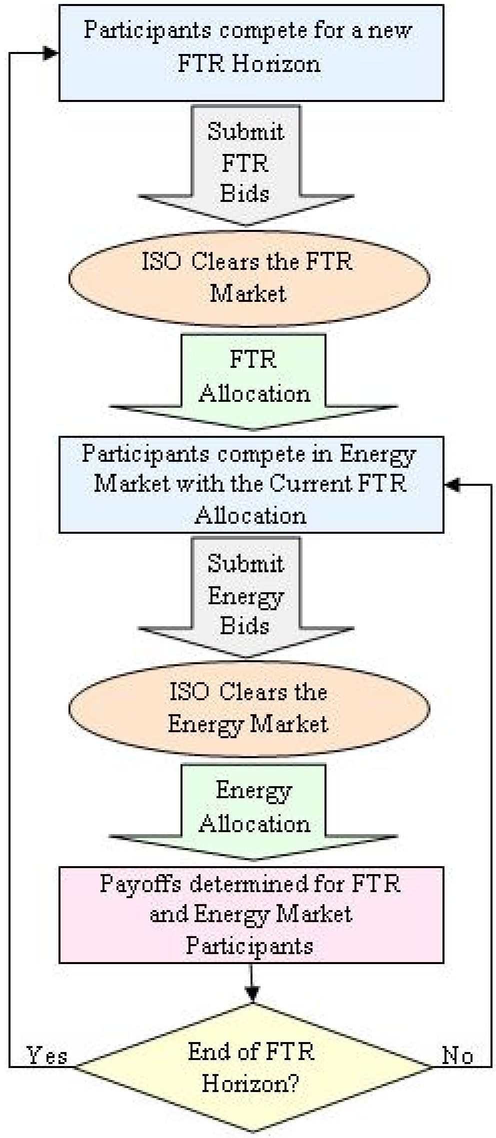

Figure 4.1 FTR and Energy Market Operation Cycle

4.1 A Matrix Game Model for Joint FTR and Energy Market Settlement

Let $\mathcal{I} = \{1, 2, \cdots, I\}$ denote the set of paths of injection and withdrawal locations for which FTRs can be obtained. Let $\mathcal{N} = \{1, 2, \cdots, N\}$ denote the set of bidders participating in the joint market some of whom are generators denoted by set $\mathcal{G}$, and loads denoted by set $\mathcal{L}$ where: $\mathcal{G} \subset \mathcal{N}$ and $\mathcal{L} \subset \mathcal{N}$. Also, let $\mathcal{S}$ be the set of actions in the joint market. A bidder $n \in \mathcal{N}$ is considered to bid on a subset of paths $\mathcal{I}_n \subset \mathcal{I}$ in FTR market with an action $a_n^i \in \mathcal{S}_n^i$ for each path where: $\mathcal{S}_n^i$ is the set of strategies available to bidder n on path i. It is assumed that loads have inelastic (constant) demands, therefore, only generators compete in energy market. A generator $g \in \mathcal{G}$ is considered to bid with a strategy $a_g \in \mathcal{S}_g$ where: $\mathcal{S}_g$ denotes the set of available actions for generator g in energy market.

The cycle of FTR and energy market operations is given in Figure 4.1. A matrix game model is used to solve the non-cooperative competition among bidders. A schematic diagram of the steps of the joint matrix game model is presented in Figure 4.2. Initial step (step 0) is to define the network parameters such as the set of FTR paths of each bidder, generation cost functions of suppliers, contingency and demand scenario probabilities and strategy space of the bidders. At step 1, we initialize the strategies of all bidders to the first strategy in their strategy set. Step 2-4 and 14-17 is to cover all strategy combinations by the participants on all their paths in FTR market. At the end of each strategy combination, FTR market is settled by the ISO at step 5. After allocating FTRs to the participants in step 5, algorithm continues with the energy market operations starting with initializing the strategies of all generators to the first strategy in their energy strategy set (step 6). Steps 7-8 and 11-12 are to explore all the possible energy strategy combinations by the generators. At the end of each strategy combination, ISO settles the energy market and determines the generation quantities by the generators together with the bus LMPs (step9). At step 10, the model is ready to calculate the payoffs of the generators for the corresponding strategy combination. After computing the payoffs of generators, it is transferred to energy payoff matrix which is completed at the end of step 12. At step 13, equilibrium strategy in the energy market is found by RL algorithm for the current FTR allocation. This equilibrium point is used not only to calculate the payoffs of the generators but also loads who compete in FTR market (step 14). This cycle continues until all the FTR strategies are visited and corresponding payoffs are transferred to FTR payoff matrix (end of step 17). At step 18, RL algorithm is used to find the equilibrium strategy in the FTR market.

The value iteration based reinforcement learning algorithm to find the equilibrium strategy in both markets is explained in Section 3.2. Details about the strategy vectors of the bidders, ISO's settlement models and calculation of the payoffs in both FTR and energy market is discussed in Section 4.2.

4.2 A Matrix Game Model Formulation for Joint Market Settlement

In this section, bid vector of participants are presented for both FTR and energy markets. Participants compete with each other by submitting bids to ISO which settles the market for the given bids. ISO's market settlement models are also given together with payoff calculations of the bidders.

4.2.1 FTR Allocation Model Formulation

A bidder n submits her FTR benefit function which is a non-decreasing quadratic concave function defined as $f_n(X) = \beta_n X_n - \tau_n X_n^2$ where: X_n is the quantity of FTR either in form of obligation or option. Therefore, the bidder is required to submit a linear parameter and a quadratic parameter for her benefit function, and the type of FTR to ISO for FTR auction. Thus, a bid vector for bidder n on path $i \in \mathcal{I}_n$ can be denoted as

$$a_n^i = \left(\beta_n^i;\ \tau_n^i;\ k_n^i\right),$$

where

β_n^i	n^{th} bidder's linear price bid on FTR path i,
τ_n^i	n^{th} bidder's quadratic price bid on path i,
k_n^i	n^{th} bidder's FTR type selection on path i valued 1 for obligation and 0 for option type.

After participants submit their bids for FTR auction, ISO allocates the FTRs based on an optimization model with an objective of revenue maximization (Step 5 in Figure 4.2). This dc model can be given as follows.

$$max \sum_{n=1}^{N} \sum_{i \in \mathcal{I}_n} \beta_n^i * (FTR_n^{i,ob} + FTR_n^{i,op}) - \tau_n^i * (FTR_n^{i,ob} + FTR_n^{i,op})^2 \tag{4.1}$$

s.t.

$$\sum_{n=1}^{N} \sum_{i \in \mathcal{I}_n} [D_{n,l}^{i,c} * FTR_n^{i,ob} + max(0, D_{n,l}^{i,c}) * FTR_n^{i,op}] \leq B_l^c \quad \forall\, l,\ c \tag{4.2}$$

$$\sum_{n=1}^{N} \sum_{i \in \mathcal{I}_n} [-D_{n,l}^{i,c} * FTR_n^{i,ob} + max(0, -D_{n,l}^{i,c}) * FTR_n^{i,op}] \leq B_l^c \quad \forall\, l,\ c \tag{4.3}$$

$$FTR_n^{i,ob} \leq k_i^n * M \quad \forall\, n,\ i \tag{4.4}$$

$$FTR_n^{i,op} \leq (1 - k_i^n) * M \quad \forall\, n,\ i \tag{4.5}$$

where

$FTR_n^{i,ob}$	quantity of obligation FTR allocated to n^{th} bidder on path i (decision variable)
$FTR_n^{i,op}$	quantity of option FTR allocated to n^{th} bidder on path i (decision variable)
$D_{n,l}^{i,c}$	PTDF of the n^{th} bidder's i^{th} path on line l under contingency c
B_l^c	capacity limit of line l under contingency c
M	big-M value used to constrain allocation of FTR only to the selected type

ISO's FTR revenue maximization model determines the FTR allocation and corresponding costs for all participants. FTR cost of a bidder n who is bidding with (β_n^i, τ_n^i, k_n^i) strategy vector on her FTR paths $\mathcal{I}_n$ is calculated as

$$FC_n = \sum_{i \in \mathcal{I}_n} \beta_n^i (FTR_n^{i,ob} + FTR_n^{i,op}) - \tau_n^i (FTR_n^{i,ob} + FTR_n^{i,op})^2.$$

Although FTR costs are calculated at the end of FTR auction, ISO has to clear the energy market before FTR revenues can be calculated, i.e., energy settlement data are needed to compute FTR revenue. Therefore, computation of FTR revenue and profit are explained in the following section.

4.2.2 Energy Allocation Model Formulation

Generators have marginal (real) cost functions which are assumed to be quadratic convex functions defined as $h_g(Z_g) = \gamma_g^o Z_g + \eta_g^o (Z_g)^2$ where: Z_g is the quantity of electricity supplied by generator g. However, generator $g \in \mathcal{G}$ submits her energy cost function as $h_g(Z_g) = \gamma_g Z_g + \eta_g (Z_g)^2$ where linear and quadratic cost coefficients are part of her strategy to maximize her payoff. The generator also has to submit the lower and upper bound (capacity) of her power generation. Therefore, a generator is required to submit a linear cost parameter, a quadratic cost parameter, lower production limit, and upper production limit to ISO for energy auction. Thus, a bid vector for generator g can be denoted as

$$a_g = (\gamma_g;\ \eta_g;\ \underline{p}_g;\ \overline{p}_g),$$

where

γ_g	g^{th} generator's linear cost bid,
η_g	g^{th} generator's quadratic cost bid,
$\underline{p}_g$	g^{th} generator's lower generation limit,
$\overline{p}_g$	g^{th} generator's generation capacity.

After participants submit their bids for energy auction, ISO determines the power supply among the generators based on an optimization model with an objective of cost minimization of supplying power to consumers (Step 9 in Figure 4.2). There are two random factors in the ISO's model that is ascertained at the time of energy auction:

1. Contingency situation

2. Demand situation

ISO clears the energy market based on the current contingency situation and consumer demands. It is assumed that there are C contingency scenarios of lines and U demand scenarios of loads. Let $c \in \{1, 2, \cdots, C\}$ denote the current contingency scenario and $u \in \{1, 2, \cdots, U\}$ denote the current demand scenario. Also, let $b \in \mathcal{B}$ denote the buses, $ij \in \mathcal{A}$ denote the arcs (directed lines), and $m \in \mathcal{R}$ denote the transmission line loops present in the network. All the arcs that are in loop m are denoted by the set $\mathcal{A}_m$. Similarly, all the generators (loads) that are located at bus b are denoted by

$\mathcal{G}_b$ ($\mathcal{L}_b$). Then ISO's energy settlement model can be given as follows.

$$min \sum_{g \in \mathcal{G}} \gamma_g * Z_g + \eta_g * Z_g^2 \tag{4.6}$$

s.t.

$$\sum_{g \in \mathcal{G}_b} Z_g - Q_b^u + \sum_{b:ib \in \mathcal{A}} T_{ib} - \sum_{j:bj \in \mathcal{A}} T_{bj} = 0 \qquad \forall\ b \tag{4.7}$$

$$\sum_{ij \in \mathcal{A}_m} s_{ijm} T_{ij} = 0 \qquad \forall\ m \tag{4.8}$$

$$T_{ij} \leq \overline{T}_{ij}^c \qquad \forall\ ij \tag{4.9}$$

$$Z_g \leq \overline{p}_g \qquad \forall\ g \tag{4.10}$$

$$Z_g \geq \underline{p}_g \qquad \forall\ g \tag{4.11}$$

$$Z_g \geq 0; \quad T_{ij} \geq 0 \qquad \forall\ g,\ \forall\ ij \tag{4.12}$$

where

Q_b^u	total quantity of demand at bus b under demand scenario u (i.e., $Q_b^u = \sum_{l \in \mathcal{L}_b} q_l^u$)
Z_g	quantity of electricity supplied by generator g (decision variable)
T_{ij}	amount of electric flow on arc ij (decision variable)
s_{ijm}	Kirchhoff voltage coefficient for arc ij in loop m, equals to 1 if ij in the same direction with the loop m and -1 if in the opposite direction with the loop m
$\overline{T}_{ij}^c$	Electric flow capacity of arc ij under the contingency scenario c

ISO's energy cost minimization model determines the allocation of power generation by suppliers to meet the demand. Energy profit of a generator g for the contingency scenario c and demand scenario u is calculated as

$$EP_g^{c,u} = LMP_{b_g}^{c,u} \cdot Z_g^{c,u} \; - \; [\gamma_g^o Z_g^{c,u} + \eta_g^o (Z_g^{c,u})^2],$$

where: $LMP_{b_g}^{c,u}$ denotes the LMP at the bus where generator g is located. Loads do not compete in energy market, however, they make payments to the ISO based on the energy settlement data. Therefore, energy profit of a load for the contingency scenario c and demand scenario d is basically the cost of her demand which can be stated as

$$EP_l^{c,u} = \, - \, LMP_{b_l}^{c,u} \cdot q_l^{c,u},$$

where: $LMP_{b_l}^{c,u}$ denotes the LMP at the bus where load l is located. As stated in the previous section, FTR costs (FC) are computed at the end of the FTR settlement, however, energy settlement data are needed to calculate the FTR revenue of a participant. Therefore, FTR profits can be calculated at this stage together with energy profits. FTR profit of a bidder n who has a set of FTR paths $\mathcal{I}_n$ will be calculated for the contingency scenario c and demand scenario u as

$$FP_n^{c,u} = \sum_{i \in \mathcal{I}_n} [\Delta LMP_n^i \cdot FTR_n^{i,ob} + max(\Delta LMP_n^i, 0) \cdot FTR_n^{i,op} \; - \; FC_n^i].$$

In the equation above, ΔLMP's and FTR quantities are for contingency scenario c and demand scenario u. It is assumed that each of the contingency-demand scenario has a probability to occur defined with joint probability matrix $\phi(c,u)$. Since the contingency and demand scenario that will happen during the energy auction is unknown to the market participants, the average payoff value over all contingency and demand scenarios is significant. Expected payoff of bidder n for an FTR and energy settlement with different contingency and demand scenarios is

$$\widehat{PO}_n = \sum_{c=1}^{C} \sum_{u=1}^{U} \phi(c,u) \cdot (FP_n^{c,u} \; + \; EP_n^{c,u}).$$

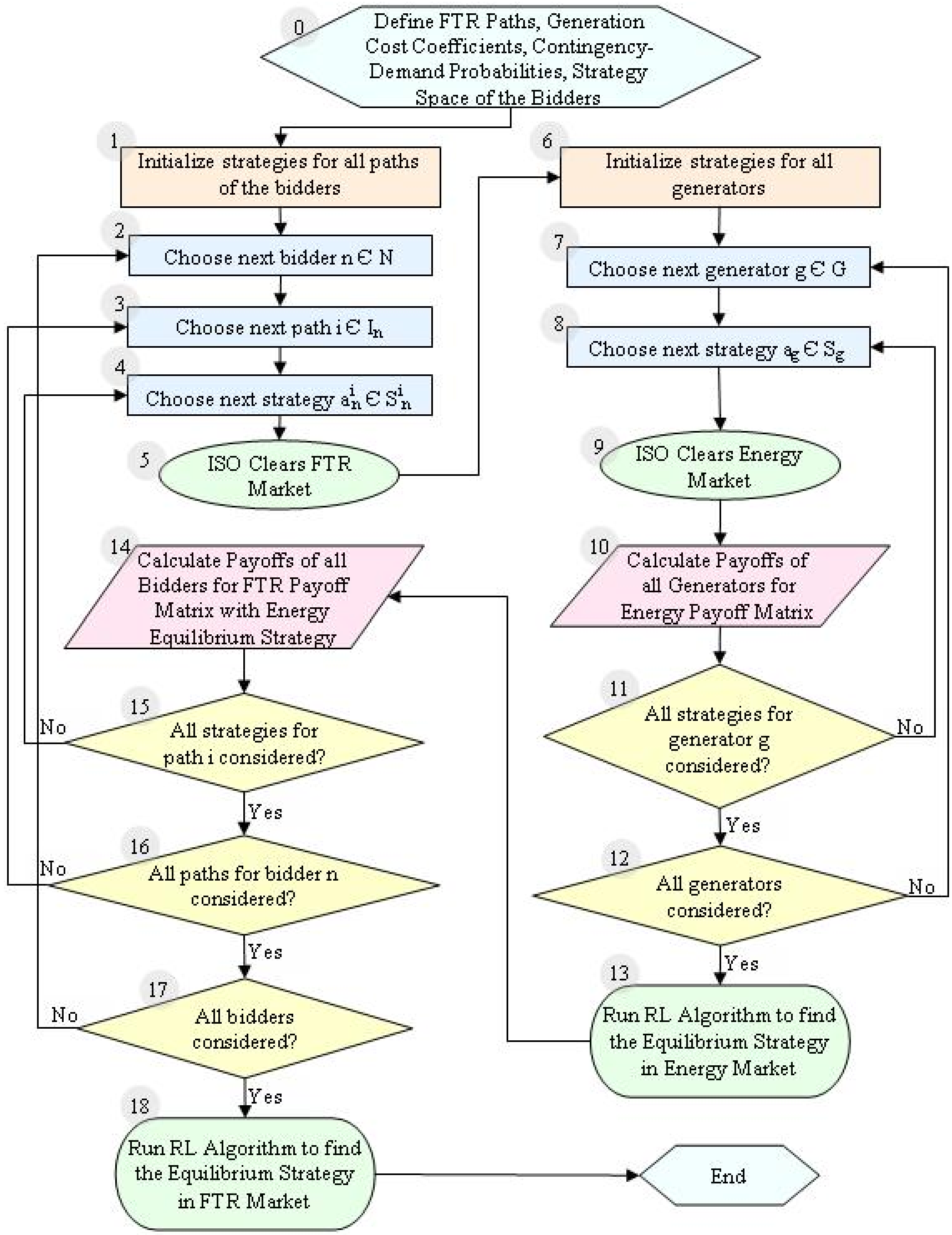

Figure 4.2 Matrix Game Model Solution Steps for Joint Market

CHAPTER 5
NUMERICAL EXAMPLE: FTR MARKET SETTLEMENT

In order to demonstrate the matrix game theoretic approach to obtain equilibrium bidding strategies for an FTR market, a sample power network, as studied in [2], was adopted. By varying the network parameters like contingencies and LMP differences between the nodes, sixteen different network scenarios are created for which equilibrium FTR bidding strategies are presented. Since in the matrix game formulation the continuous bid parameters (obligation price, option price, quantity, and type mix) are discretized, the effect of the extent of discretization is examined next. Thereafter, the impact of individual bid parameters of the bidders under the assumption that the other bidders choose their actions uniformly from the available sets is studied. Finally, the impact of the network parameters on the equilibrium FTR bidding strategies is investigated through an analysis of variance (ANOVA) via a 2^4 factorial experiment. The columns of the tables that do not have units are in generic units.

5.1 The Sample Network

The sample network consisting of three buses and four bidders is depicted in Figure 5.1. The Bidders 3 and 4 are considered non-strategic, hence only bidders 1 and 2 are considered strategic bidders in the matrix game. The paths between source and sink buses on which the bidders bid are shown in the Figure 5.1, which also indicates the reactance values and flow limits of each line.

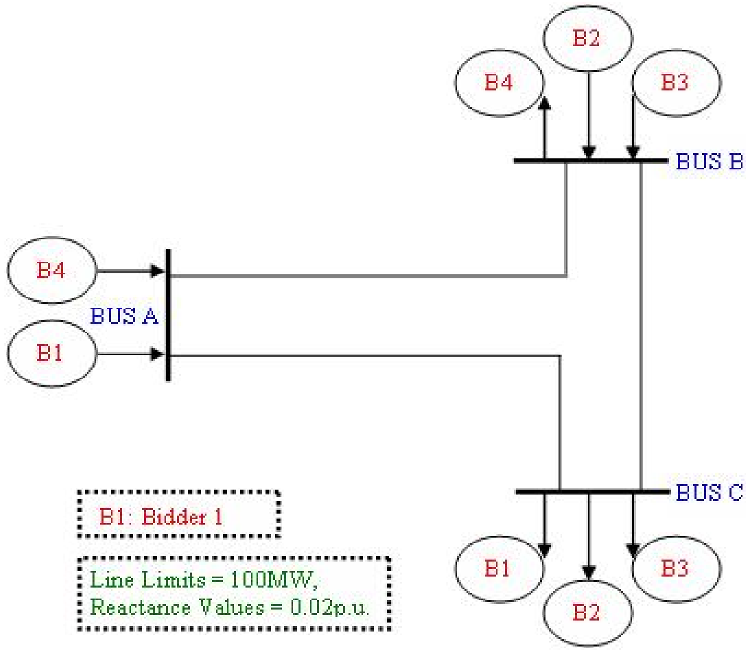

Figure 5.1 FTR Bidders in a 3-Bus Power Network

5.2 Equilibrium Bidding Strategies for Different Network Scenarios

Four key network related parameters that were considered in this study are contingency (**c**), ΔLMPs (**l**), variances of the ΔLMP estimates (**v**), and the risk coefficient (**r**). Sixteen different network scenarios were created by varying each of the four network parameters at two levels. The parameters l, v, $and\, r$ (which could be varied for both strategic bidders) were varied only for bidder 2. In order to simplify the numerical exposition, the obligation and the option price bids are considered to be identical, which reduced the size of the bid vector from four to three dimensions. It is noted however, that obligation FTR may become a liability, whereas the option FTR does not have such a risk, and hence the bid prices could be different. Our model is general and accommodates this characteristic. For each of the sixteen scenarios, the possible number of bid choices of the two players was kept constant at 125 with five levels of discretizations for each of price, quantity, and the type mix. Table 5.1 shows the

Table 5.1 Network and Bid Values

Network Parameters	*Bidder 1 Values*	*Bidder 2 Values*	
		Low	*High*
ΔLMP (l)	20	9	13
Variance (v)	0.2	0.1	2
Risk Coefficient (r)	0.003	0.001	0.01
Contingency (c)	Low→No Contingency, High→Line 1 out		
Bidding Parameters	*Discretization Levels*		
Price	(0.5, 0.7, 0.8, 0.9, 0.95)		
Quantity	(0.3, 0.4, 0.5, 0.7, 0.9)		
FTR-type Mix	(0, 0.25, 0.50, 0.75, 1)		

values of the network and the bid parameters. For each scenario, the payoff matrices were constructed and the value iteration based learning algorithm was implemented. The network scenarios and the corresponding pure strategy equilibrium as obtained by the RL algorithm are presented in Table 5.2.

As indicated in the last column of Table 5.2, in ten out of the thirteen scenarios having pure strategy Nash equilibria, the RL algorithm converged to a Nash equilibrium point. Among the multiple Nash equilibria that exist for scenarios **vr** and **clvr**, the strategies that the RL algorithm converged to have higher payoffs for both bidders compared to the other Nash equilibrium points. In three of the remaining scenarios (with *'No'* in the last column), the RL algorithm converged to non-NE strategies yielding higher payoffs for both of the bidders compared to the NE payoffs. Recognizing these solutions is critical since all bidders must accept to stay at these points in order to gain the benefits of these higher than Nash equilibrium payoffs. For these scenarios, Table 5.3 shows a comparison of the payoffs from the Nash equilibrium strategies and the corresponding non-NE strategies obtained by the RL algorithm. The remaining three scenarios (with a **'-'** in the last column) do not have a pure

Table 5.2 Equilibrium Bidding Strategies for Sixteen Network Scenarios

Network Scen.	*Equilibrium Bidding Strategy by RL Algorithm*								*Nash Equili*
	Strategy of Participant 1				*Strategy of Participant 2*				
	Price	*Quantity*	*Type-Mix*	*Payoff*	*Price*	*Quantity*	*Type-Mix*	*Payoff*	
(1)	0.9	0.7	0.75	286.49	0.9	0.7	0.25	0	*Yes*
c	0.8	0.7	1	394	0.8	0.5	0	179	*Yes*
l	0.9	0.3	0.25	175.14	0.7	0.7	0.25	427.79	*No*
cl	0.8	0.5	1	198.5	0.7	0.5	0.25	582.75	-
v	0.9	0.9	0	286.49	0.9	0.3	0	0	*Yes*
cv	0.8	0.4	0.25	394	0.8	0.9	0.25	160	*Yes*
lv	0.9	0.3	0	175.14	0.7	0.4	0.5	404.8	*No*
clv	0.8	0.5	0	316.16	0.7	0.4	0	439.2	-
r	0.9	0.7	0.75	286.49	0.95	0.9	0.25	0	*Yes*
cr	0.8	0.4	0.5	394	0.8	0.7	0.75	170	*Yes*
lr	0.9	0.3	0.25	175.14	0.7	0.4	1	416.9	*No*
clr	0.9	0.3	1	175.14	0.7	0.5	0.25	416.9	-
vr	0.8	0.4	0.25	394	0.8	0.3	0.5	0	*Yes*
cvr	0.8	0.4	0.25	394	0.5	0.3	0	0	*Yes*
lvr	0.9	0.4	0.25	194	0.7	0.4	0.25	190	*Yes*
clvr	0.8	0.9	0.75	394	0.7	0.3	0	189	*Yes*

Legend: *(1)* : All parameters (l,v,r,c) set at low level; *cl* : contingency and ΔLMP at high level, covariance and risk coefficient at low level; *clvr* : all parameters at high level; a dash (**-**) in the last column indicates non-existence of pure strategy Nash equilibrium

Table 5.3 Strategies with Higher Payoffs than Nash Equilibrium

Network Scenarios	NE Equilibrium		RL Equilibrium	
	Bidder 1 Payoff	Bidder 2 Payoff	Bidder 1 Payoff	Bidder 2 Payoff
l	94	259	175.14	427.79
lv	94	240	175.14	404.8
lr	94	250	175.14	416.9

strategy Nash equilibrium. The RL algorithm converged to strategies with a high payoff distribution for the bidders.

5.3 Impact of Bid Parameter Discretization

As discussed earlier, discretization of the bid parameters is essential to formulating the non-cooperative behavior of the bidders as a matrix game. A finer discretization of the continuous parameters is required to minimize the deviation from the actual problem scenario and the true equilibrium. At the same time, finer discretization of the parameters of a multidimensional bid vector expands the action space, which increases the dimensions of the payoff matrices and the resulting computational requirements.

In order to expose the significance of discretization, the impact of price parameter discretization on the equilibrium bidding strategies is studied. Five different levels of discretization of the price parameter $(3, 5, 10, 15, and\ 20)$ were considered while the discretization of quantity and type mix parameters were kept constant at 5 levels each. This resulted in payoff matrix sizes varying from 75×75 $(3 \times 5 \times 5)$ to 500×500 $(20 \times 5 \times 5)$. The equilibrium payoffs of the players are given in Table 5.4. As evident from the payoffs, the equilibrium strategies varied quite significantly with the level of discretization. It also appears that with finer price discretization the payoffs of the bidders increased. This is due to the fact that the algorithm always looks for an equilibrium with high *values*, and as discretization increases, the algorithm has more candidates to choose from.

Table 5.4 Impact of Bid Parameter Discretization

Level of Discretization			RL Equilibrium Payoff	
Price	Quantity	Type Mix	B1	B2
3	5	5	111.36	124.55
5	5	5	111.36	124.55
10	5	5	194	101
15	5	5	254	132.5
20	5	5	294	153.5

5.4 Impact of Bid Parameter Variations

The equilibrium outcome of a matrix game is a resultant of the parameter values of the participants' bid vectors. Though it is difficult, it is desirable to extract insight into the impact of the individual bid parameter on the equilibrium payoffs. Therefore, an experiment where impact of each bid parameter was graphically analyzed is conducted as follows. It is acknowledged that the observations made in this section have problem specific interpretations with some potential for generalization. In the experiment, the network parameter values were maintained at the following. For bidder 1: ΔLMP = \$20, variance = 0.2, risk coefficient = 0.003, and for bidder 2: ΔLMP = \$10.5, variance = 0.2, risk coefficient = 0.002. Maximum quantity (Q) was considered to be 300, and the network was assumed to have no contingency. The price factor of bidders 1 and 2 were varied in ten steps between 0.1 and 0.95 in steps of 0.1. Figure 5.2 shows the impact of price variations by bidder 2 on bidder 1 payoffs. The payoffs of bidder 1, as plotted, were averaged over all possible combinations (80×80) of quantity and type mix parameters of the two bidders, where each bidder has 10×8 possible bid choices. For all bidder 1 price factor values up to 0.7, the payoff was zero. For bid price factor beyond 0.7, bidder 1's payoffs were identical for all bid price factors less than or equal to 0.7 by bidder 2. Hence, only the bid price factor scenarios with both bids greater than or equal to 0.7 are critical as shown in Figure 5.2. As bidder 2 changes its price factor, the optimal price bid for bidder 1 also changes. For example, as bidder 2 changes price factor from 0.7 to 0.8, the optimal price bid for bidder 1 changes from 0.8 to 0.9. Similarly, Figure 5.3 shows the impact of price bid variations of bidder 1 on the bidder 2's payoffs (utility). A general conclusion that can be drawn from the above is that a significant interaction exists between the bidder prices in how they impact the bidder utilities. The exact level of interactions will depend on the network parameter values.

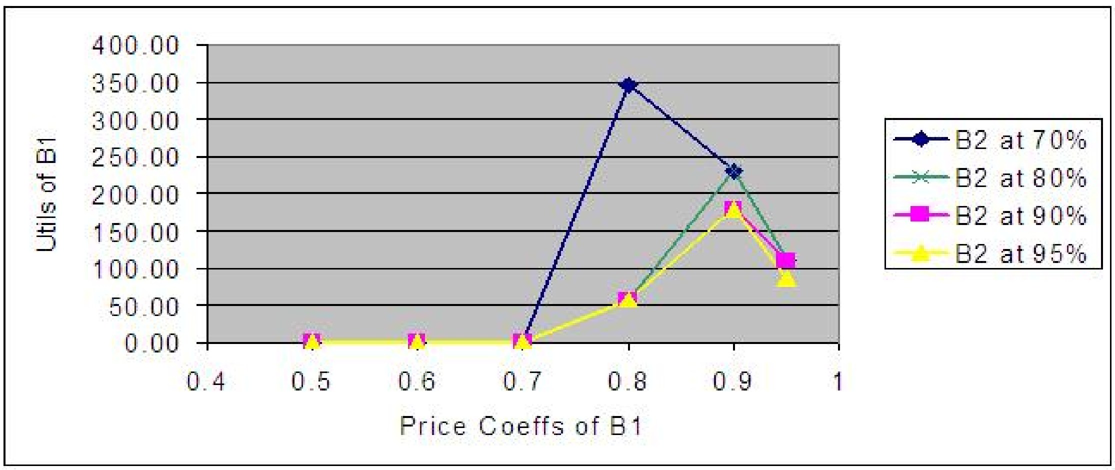

Figure 5.2 Price Effect on Bidder 1's Average Utility

Analyses, similar to that of price, were also conducted with quantity and type mix parameters. The results from the investigation of the quantity parameter are presented in Figures 5.4 and 5.5. For both bidders, the quantity effect appears to be somewhat identical. The bidder payoffs increase with increase in the quantity bid, and they level off after 0.5 for bidder 1 and 0.7 for bidder 2 irrespective of the competitor's bid. This indicates that for the given problem parameters, the quantity bid should be kept at the maximum possible value. However, it was our conjecture that in the

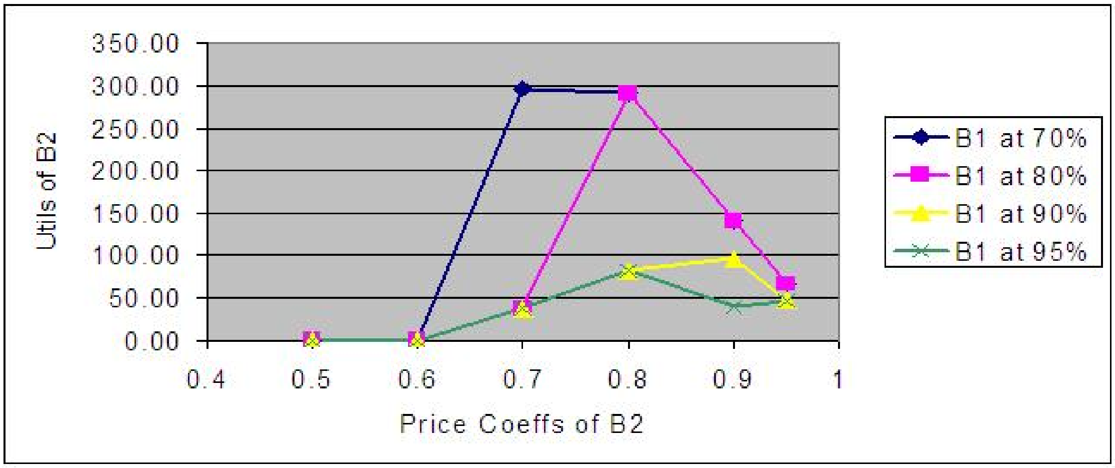

Figure 5.3 Price Effect on Bidder 2's Average Utility

presence of high values of variance and/or risk coefficient, the choice of the quantity parameter could become strategic. To test this conjecture, the sample network was studied under a new scenario with the following network parameters. For bidder 1: ΔLMP = \$20, variance = 0.2, risk coefficient = 0.003, and for bidder 2: ΔLMP = \$13, variance = 2, risk coefficient = 0.01. The strategic impact of bidder 2's quantity bid on her payoff, which starts to decline beyond a certain value of quantity bid, is shown in Figure 5.6. This is in clear contrast to the *higher the better* behavior seen earlier. A general conclusion can be stated that FTR quantity could be a significant parameter and should be considered in the bidding process.

The results of the investigation on the impact of type mix parameter on the bidder payoffs are given in Figures 5.7 and 5.8. It appears from Figure 5.7 that bidder 1's payoff is not affected by its choice of the type mix parameter, and is only minimally affected by the choice of bidder 2's type mix parameter. On the other hand, bidder 2s payoff is completely independent of bidder 1's strategy, as evident from the overlapping curves in Figure 5.8. Bidder 2 suffers a significant decrease in utility with the choice of higher values of the type mix factor (i.e., higher proportion of

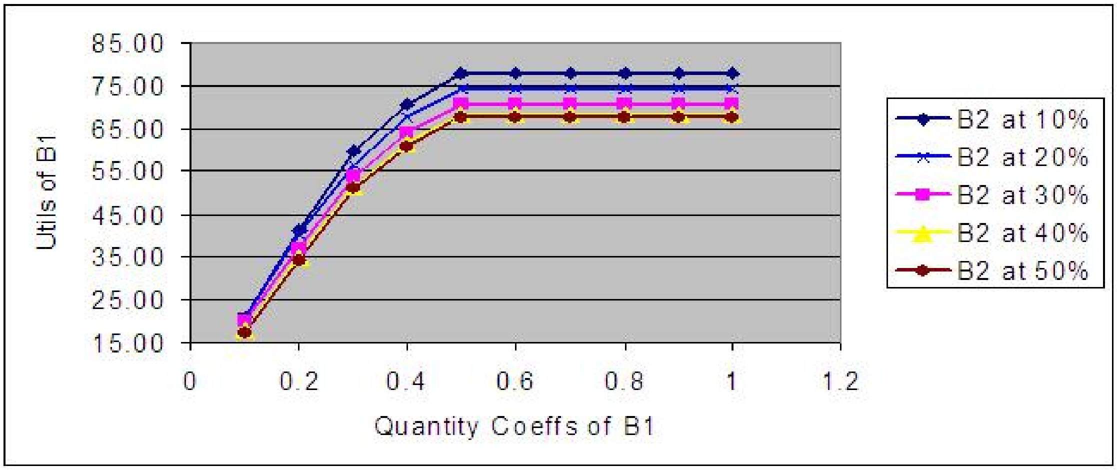

Figure 5.4 Quantity Effect on Bidder 1's Average Utility

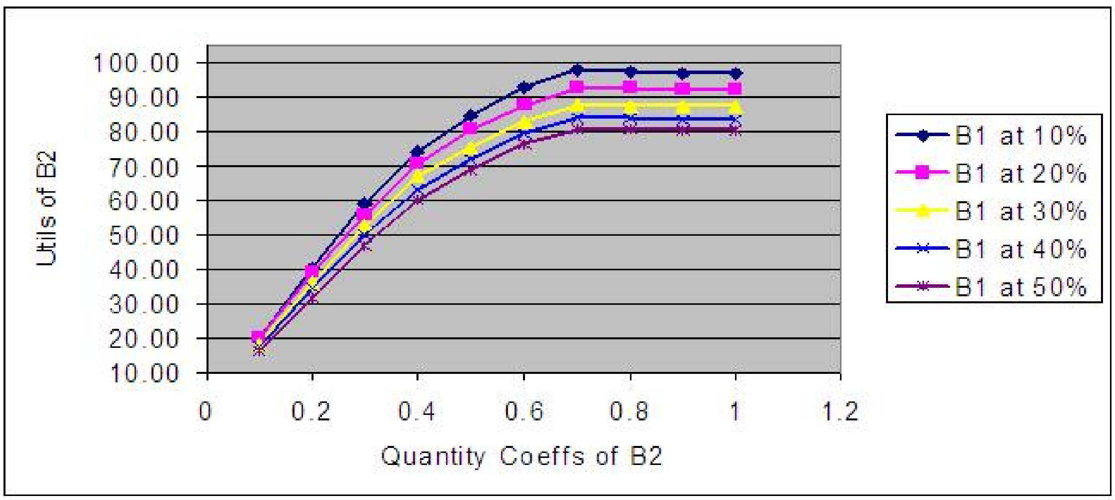

Figure 5.5 Quantity Effect on Bidder 2's Average Utility

obligation). Table 5.5 depicts, for a sample scenario, how the total FTR allocation as well as its obligation and option components change for bidder 2, as the bidder varies its type mix bid. This supports the trend observed in Figure 5.8, since bidder 2 wins the most FTR when the type mix factor is set at zero (i.e., all option), and the FTR allocation decreases as more obligations are added to the mix. It is concluded that

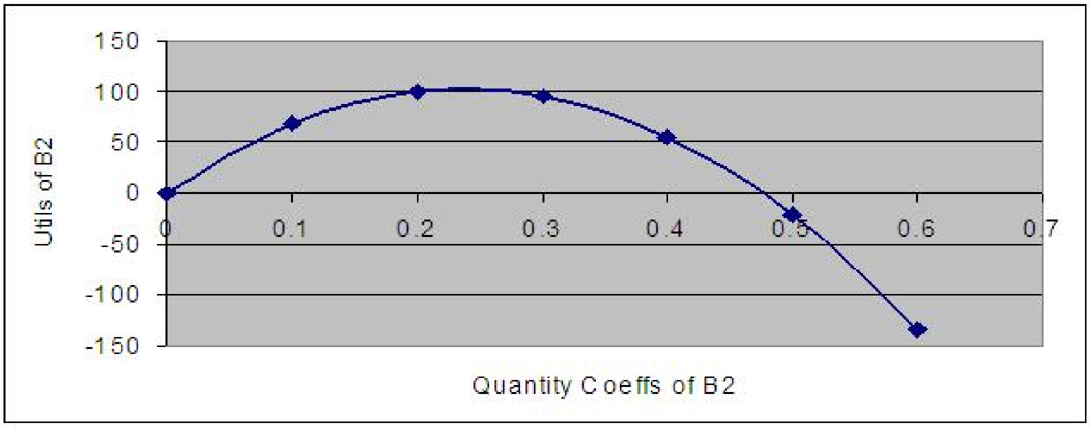

Figure 5.6 Strategic Impact of Quantity Parameter

type mix parameter could play a significant role in a multi-bidder FTR settlement process and thus should be adequately investigated.

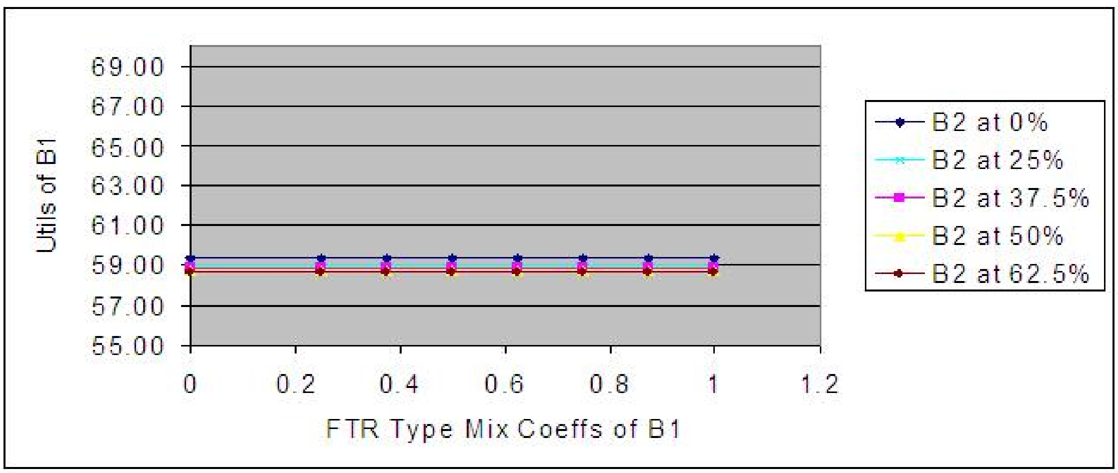

Figure 5.7 Type Mix Effect on Bidder 1's Average Utility

5.5 Impact of the Network Parameter Variations

The impact of the network parameters on the equilibrium payoffs of the bidders was studied through an analysis of variance (ANOVA) via a 4-factor designed experiment. The factors, their levels, and the sixteen (2^4) experiments were presented in

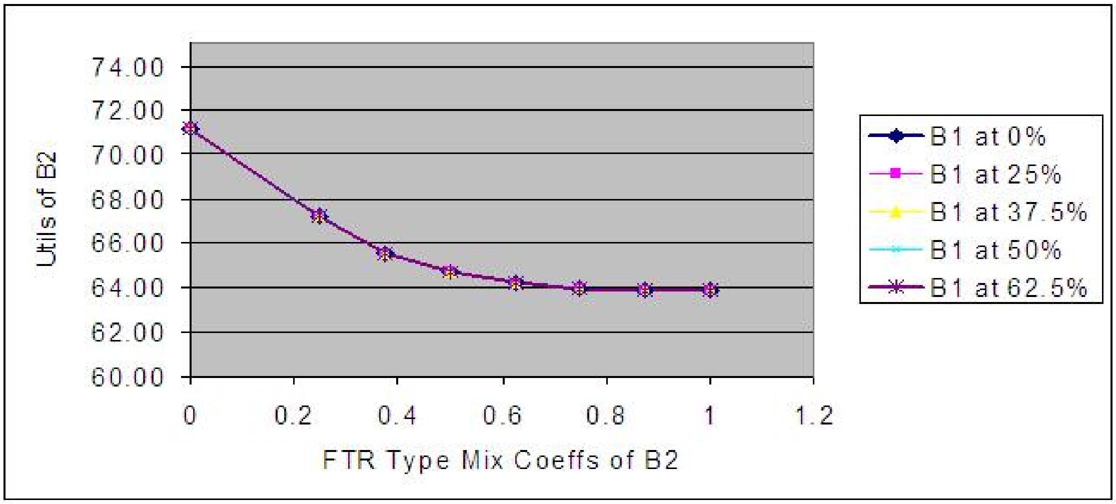

Figure 5.8 Type Mix Effect on Bidder 2's Average Utility

Table 5.5 Impact of Type Mix Parameter

B 2 FTR Type Mix	Bidder 2 (MW)		
	Obl-FTR	Opt-FTR	Total FTR
0	0	90	90
0.25	22.5	67.5	90
0.375	33.75	54.4	88.15
0.5	45	37.53	82.53
0.625	56.25	20.66	76.91
0.75	67.5	3.78	71.28
0.875	70.02	0	70.02
1	70.02	0	70.02

Table 5.1 and 5.2. Two sets of ANOVA were performed using payoffs of bidder 1 and bidder 2 (given in Table 5.2) as experimental outcomes. Since each outcome is a single replicate, normal probability plots of the factor and interaction effects were constructed to obtain error sum of square (SS) estimates. The ANOVA results are given in Tables 5.6 and 5.7. It appears from Table 5.6 that bidder 2's payoff is affected by all four of the factors and is insensitive to any of the factor interactions. Among the significant factors, the ΔLMP appears to be the most critical with a p-value of

Table 5.6 ANOVA with Bidder 2's Payoffs

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	Fo	P-Value
C	30394	1	30394.4	4.68	0.067
L	409069	1	409069.0	62.93	0.0001
V	41041	1	41040.7	6.31	0.040
CLV	284	1	284.3	0.04	0.840
R	41081	1	41081.2	6.32	0.040
LR	13968	1	13967.7	2.15	0.186
CLR	29	1	28.5	0.00	0.949
CLVR	4575	1	4575.2	0.70	0.429
Error	45506	7	6500.8		
Total	585947	15			

Table 5.7 ANOVA with Bidder 1's Payoffs

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	Fo	P-Value
C	29490	1	29490.3	8.06	0.016
L	65824	1	65824.3	17.98	0.001
CR	323	1	323.0	0.09	0.772
LR	73	1	73.0	0.02	0.890
Error	40263	11	3660.3		
Total	135973	15			

0.0001. Table 5.7 shows that, for the given network, bidder 1's payoff is affected only by the ΔLMP estimate of bidder 2 and the contingency in the network. As expected, variance and risk coefficient parameters of bidder 2 (which are the other two factors considered in the experiment) have no significant impact on the payoff of bidder 1.

CHAPTER 6

NUMERICAL EXAMPLE: JOINT FTR AND ENERGY MARKET SETTLEMENTS

In order to demonstrate the matrix game theoretic approach to obtain equilibrium bidding strategies for joint FTR and energy markets, a sample power network is adopted. First, impact of the FTRs on the strategies of a bidder is investigated by assigning a different FTR path to the bidder. FTR effects have also been analyzed by comparing the payoffs of participants with and without FTRs. Thereafter, the impact of the contingency and demand variations in the electric market to the equilibrium market point has been examined by changing the frequencies of contingency and demand scenarios. Finally, the impact of generators' marginal cost function on the equilibrium bidding payoffs has been studied by varying the cost functions for some generators. The columns of the tables that do not have units are in generic units.

6.1 The Sample Network

The sample network chosen to examine the joint market is PJM 5-bus example in which there are five generators and three loads. The location of each generator and load together with the transmission lines and their reactance values are depicted in Figure 6.1.

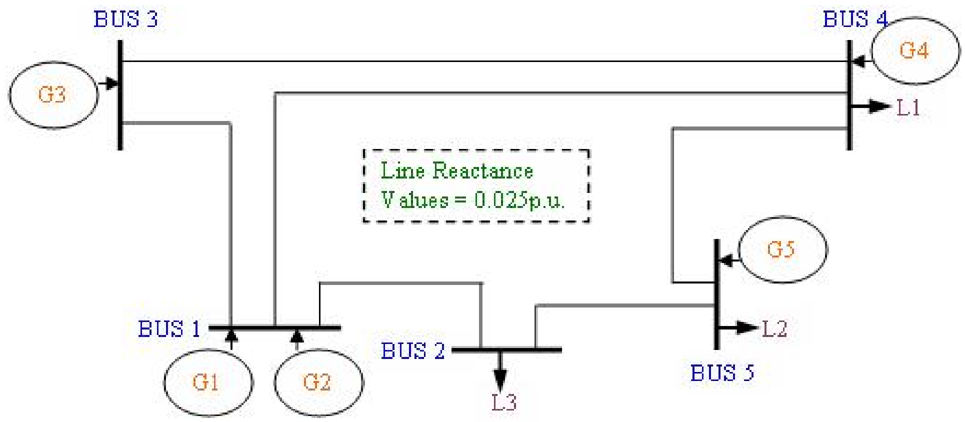

Figure 6.1 PJM 5-Bus Power Network

6.2 Impact of FTRs in Market Settlement

The impact of FTRs on the bidding strategies of participants has been studied by assigning certain quantities of FTR on different paths. Only one bidder is selected and certain FTR quantities are allocated to this bidder on different FTR paths one at a time. To simplify the experiment and single out the FTR effect, other participants are not allocated any FTRs. Generators compete with each other by changing their strategies and finally an equilibrium point is reached through RL algorithm.

In this experimentation, generator 1 is chosen to hold the FTR on varying path scenarios which are given in 6.1. The bidding parameters and factors of generators for energy market is shown in Table 6.2. For example, if generator 4 selects second linear strategy and second quadratic strategy to bid then generator 4's cost function will be $h(Z_4) = 1.4 * 30 * Z_4 + 1.2 * 0.025 * Z_4^2 \;\; where \;\; 0 \leq Z_4 \leq 200$. As seen in Table 6.2, any generator who bids with the first linear and quadratic strategy in fact bids less than her marginal cost function. This characteristic is integrated in the bidding model to enlarge bidding space of a bidder. For example, a bidder may accept to lose energy revenue in return of high FTR revenue. Bidding parameters in the table are

Table 6.1 Equilibrium Bidding Strategy of Generator 1 and Bus LMPs

	FTR Path	Quantity (MW)	G1 Nash Eq. Str.		LMP at Bus 1 ($)	LMP at Bus 2 ($)	LMP at Bus 3 ($)	LMP at Bus 4 ($)	LMP at Bus 5 ($)
			Linear	Quadratic					
g1	No	0	0.9	1.2	59.9	79.0	22.3	90.2	86.3
	1-2	150 ob	0.9	0.8	59.9	79.1	22.3	90.2	86.3
	2-1	150 ob	2	1.2	60.1	78.6	22.3	90.3	86.1
	5-4	150 ob	2	1.2	60.1	78.6	22.3	90.3	86.1
	4-5	150 ob	0.9	0.8	59.9	79.1	22.3	90.2	86.3

Table 6.2 Bidding Parameters and Factors of Generators

	min(p)	*max(p)*	β	τ
g1	0	110	14	0.0140
g2	0	100	14	0.0140
g3	0	600	10	0.0025
g4	0	200	30	0.0250
g5	0	520	40	0.0250
	Linear Strategy Factors			
	0.9	1.4	2	
	Quadratic Strategy Factors			
	0.8	1.2		

similar to PJM 5-Bus example and basically exhibits the idea of having loads with expensive local generation and cheaper generation in other further buses. A generator has total of six strategy combinations (3 linear × 2 quadratic factors). For each FTR path scenario, the equilibrium strategy of generator 1 and the corresponding LMPs at each bus are presented in Table 6.1 including the no FTR case. The cost of $150MW$ FTR is assumed to be $2400. All the equilibrium points reached for different FTR path scenarios have the property of pure Nash equilibrium.

As seen in Table 6.1, generator 1 has little effect on the LMPs which change minimally between generator 1's minimum price strategy, (0.9, 0.8), on path $1-2$, and her maximum price strategy, (2, 1.2), on path $2-1$. When the different FTR scenarios at Table 6.1 are examined, it is observed that generator 1 chooses the strategy combination that maximizes its sum of energy profit and FTR profit. For example, when generator 1 competes without FTR, electric market settles down with generator 1 having $(0.9,\ 1.2)$ strategy for her linear and quadratic price factors and LMP of \$59.9 at her bus, bus 1. However, when generator 1 is allocated an obligation FTR of $150MW$ on path $1-2$, the market settles on an equilibrium point with generator 1 having $(0.9,\ 0.8)$ strategy. By changing her strategy from $(0.9,\ 1.2)$ to $(0.9,\ 0.8)$, generator 1 does not increase her energy revenue since LMP at bus 1 remains same at \$59.9, however, generator 1's FTR revenue increases due to ΔLMP_{1-2} increase. On the other hand, if the direction of FTR is reversed, i.e., selecting path 2-1, obligation FTR becomes a liability. Generator 1 adopts to this condition by switching her equilibrium strategy factor to $(2,\ 1.2)$. As a result, not only ΔLMP_{2-1} improves but also her energy revenue increases by a rise at the bus 1 LMP. As presented in Table 6.1, when FTR path $5-4$ is allocated to generator 1, she stays at the same strategy of $(2,\ 1.2)$. As a result, LMP at bus 1 continues to be \$60.1 and ΔLMP_{5-4} is \$4.2. Whereas, if FTR path $4-5$ is allocated to generator 1, generator 1 has a conflicting strategy outcomes. If generator 1 chooses the strategy of $(0.9,\ 0.8)$, she receives a smaller FTR liability ($\Delta LMP_{4-5} = \$-3.9$) but her energy revenue decreases with LMP of \$59.9 at bus 1. If generator 1 attains the strategy of $(2,\ 1.2)$, she gets a higher energy revenue with LMP of \$60.1 but FTR liability increases with a ΔLMP_{4-5} of $\$-4.2$. As stated earlier, generator 1 chooses the strategy which maximizes her overall payoff. Expected quantity of electricity that generator 2 supplies is $109.5MW$ when generator 1 selects strategy $(0.9,\ 0.8)$, and $102.6MW$ when generator 1 chooses $(2,\ 1.2)$. As a result, her overall payoff for the $(0.9,\ 0.8)$ strategy is $109.5 * 59.9\ +\ 150 * (-3.9)\ =\ \$5975.3$ and for the $(2,\ 1.2)$ strategy is $102.6 * 60.1\ +\ 150 * (-4.2)\ =\ \$5533.3$. Therefore, generator 1 chooses the strategy of $(0.9,\ 0.8)$.

Table 6.3 Equilibrium Payoffs without FTR and with FTRs

	Equilibrium FTR Allocation (MW)				Equilibrium Payoff	
	1-5	3-2	3-4	3-5	No FTR	with FTR
g1	418.64 ob				4877	2078
g2		50.24 ob			4424	4948
g3			101.37 ob		4431	6498
g4					10191	9878
g5					6324	5943
l1			101.37 ob		-27347	-23271
l2				0	-25842	-25278
l3					-23668	-23272

In order to assess the overall impact of FTRs, FTRs are made available to some of the participants simultaneously and corresponding equilibrium payoffs have been compared with the payoffs of no FTR case. Results are given in Table 6.3. The shaded cells in the table indicates the FTR path that the corresponding participant bids to acquire FTR. To increase the computational performance, participants have discretized price bid strategies starting at a minimum value.

Table 6.3 shows that generator 2, 3 and load 1 raise their payoffs when they hold FTRs. Their equilibrium FTR bidding strategies also indicate that they are willing to buy the corresponding FTRs, i.e., their price bids are higher than the minimum price bid strategy. Load 2's equilibrium price bid is also higher than the minimum price strategy. Thus, load 2 is willing to attain the FTR on path 3-5, however, ISO which has an objective of maximizing FTR sales revenue, does not allocate any FTR to load 2 with the given bid. On the other hand, load 2 does not find it profitable to bid more than her current bid which is less than her maximum price bid. Generator 1 is the only participant who bids minimum price for her FTR. The reason can be seen at her decreasing equilibrium payoff while holding FTR, i.e., generator 1 does not find it beneficial to posses this FTR path even with the minimum price bid. Finally, the change in the payoffs of the participants that do not hold any FTR is in the mixed direction. While generator 4 and 5 see a decrease in their payoff, load 2 and 3 see a small increase. It appears that existence of FTRs make the generators bid more competitively in the energy market which decrease the revenue for generators and cost for loads.

6.3 Impact of Contingency and Demand Scenario Variability

To study the effect of contingency and demand scenarios variability on the market equilibrium payoffs, four sets of joint probability matrix ($\phi(c, u)$) are generated. These matrices which are created as 2^2 factorial design, are shown in Table 6.4. Both factors (contingency variability, demand variability) have low level and high level. Notations used in this table are as follows

1. Low level of contingency variability and low level demand variability ((1))
2. Low level of contingency variability and high level of demand variability (d)
3. High level of contingency variability and low level of demand variability (c)
4. High level of contingency variability and high level of demand variability (dc)
5. Effect of demand variability (D)
6. Effect of contingency variability (C)
7. Joint effect of contingency and demand variability (DC)

There are four contingency scenarios and three demand scenarios. Contingency scenarios and corresponding line limits are given in Table 6.5. Contingency scenario 1 is basically there is no contingency and all the line limits are at their normal levels. Contingency scenario 2, 3 and 4 corresponds a decrease in the line limits of 12, 45 and 34, respectively. Low level for contingency variability factor means that majority of

Table 6.4 Equilibrium Payoffs for Contingency-Demand Probability Matrices

	Source of Variation			*Payoffs ($)*							
	D	*C*	*DC*	*g1*	*g2*	*g3*	*g4*	*g5*	*l1*	*l2*	*l3*
(1)	-1	-1	1	1994	-765	7486	10687	5301	-23642	-25547	-23216
d	1	-1	-1	1381	-1286	6984	9898	5933	-23549	-24729	-22444
c	-1	1	-1	3855	2163	6555	9311	7021	-22287	-26237	-24930
cd	1	1	1	3192	1536	6087	8485	7406	-21927	-25254	-24054
	Factor Effects			*Contingency Demand Joint Probability Matrices*							
g1	-638	1836	-25	*(1)*	0.765	0.0425	0.0425	*d*	0.5525	0.1488	0.1488
g2	-574	2875	-53		0.045	0.0025	0.0025		0.0325	0.0088	0.0088
g3	-485	-914	17		0.045	0.0025	0.0025		0.0325	0.0088	0.0088
g4	-807.5	-1394.5	-18.5		0.045	0.0025	0.0025		0.0325	0.0088	0.0088
g5	508.5	1596.5	-123.5	*c*	0.5850	0.0325	0.0325	*dc*	0.4225	0.1138	0.1138
l1	226.5	1488.5	133.5		0.1080	0.0060	0.0060		0.0780	0.0210	0.0210
l2	900.5	-607.5	82.5		0.1080	0.0060	0.0060		0.0780	0.0210	0.0210
l3	824	-1662	52		0.0990	0.0055	0.0055		0.0715	0.0193	0.0193

Table 6.5 Contingency Scenarios

Contingency Scenarios	*Line Limits (MW)*					
	12	13	14	25	34	45
1	400	400	250	350	240	240
2	200	400	250	350	240	240
3	400	400	250	350	240	120
4	400	400	250	350	150	240

the time it will remain in the no contingency scenario, 1. High level for contingency variability factor means that there is a higher probability for the contingency scenario to be other than no contingency scenario, i.e., frequency of line 12, 45 or 34 being down is higher. There are three demand scenarios of loads which are presented in Table 6.6. Demand scenario 1 is created to reflect a medium demand by all loads. Similarly, 2 represents a high demand, and 3 represents a low demand at the network. Low level of demand variability factor means that majority of the time the demand will remain in the medium demand scenario, 1. Similarly, high level of demand variability factor means that probability of having unusual demands such as low or high quantities will be bigger.

FTR market data are shown in Table 6.7. As seen from the table, generators 1, 2, and 3, and loads 1 and 2 compete in the FTR market. Their FTR paths in terms

Table 6.6 Demand Scenarios

Demand Scenarios	Demand Quantities (MW)		
	l1	l2	l3
1	300	300	300
2	360	360	360
3	250	200	200

Table 6.7 FTR Market Data for Contingency-Demand Variations

Bidder	FTR Source Bus	FTR Destination Bus	Benefit Fun. Lin. Param.	Benefit Fun.Qua. Param.
g1	1	5	10	0.002
g2	1	2	10	0.002
g3	3	4	10	0.002
l1	3	4	10	0.002
l2	3	5	10	0.002
	Linear Strategy Factors		Quadratic Strategy Factors	
	4	8	3	8

of source and destination buses, bidding parameters and factors of both linear and quadratic components of the benefit function are also given in Table 6.7. It is not given in the table, however, both obligation and option type FTR is available to the bidders as part of their FTR bidding strategy. If load 1 (bidder 6) chooses to bid for FTR on path $3-4$ with the second linear factor and the first quadratic factor then her benefit function will be $f(X_6) = 8 * 10 * X_6 - 3 * 0.002 * X_6^2$. Low and high levels of linear and quadratic coefficients of the benefit function allow the bidder to adjust the price on her path. If a bidder values her FTR path low then the bidder can choose first linear factor and second quadratic factor which will keep the price for that FTR low. Generators' bidding parameters and factors for energy market settlement remain same as shown in Table 6.2.

Equilibrium payoffs and factor effects of the participants for each contingency and demand variability level is given in Table 6.4. The changes in the factor effects based on source of variations are presented in Figure 6.2 for generators and in Figure 6.3 for loads. It should be noted that these payoffs are obtained after series of energy market settlements which is followed by the FTR market settlement. Each settlement is subject to ISO's allocation optimization model and participants bid strategically to maximize their overall payoffs. Therefore, they are result of the complex relations among market dynamics.

Figure 6.2 shows that increase in the demand variability reduces the payoffs of generator 1, 2, 3, and 4 whereas improves the payoff of generator 5. When demand variability increases, average demand decreases which pulls the average LMPs at the buses down resulting in lower energy revenue for generators. However, ISO allocates more power generation to generator 5 in the presence of high demand variability which offsets the lower energy revenue due to lower LMP and even increases her overall profit. Contingency variability increase has similar effect on the payoff of generator 3, 4, and 5, however, has a positive effect on the payoffs of generator 1 and 2. The LMP at bus 1 where generator 1 and 2 are located, is still low, however ΔLMPs of the FTR paths of generator 1 and 2 ($1-5$ and $1-2$, respectively) increases which increases their overall payoffs. When the load payoffs are analyzed under increased demand variability, it appears that all of them are affected positively. This is partly due to the fact that their average demand decreases and partly because of the decrease at the LMPs of their buses. It is also observed that improvement in load 1's payoff is smaller than load 2 and 3. This can be explained by the FTR that load 1 is holding, $3-4$. Whereas, this FTR path helps load 1 to increase her payoff when the contingency variability increases since ΔLMP increases on path $3-4$. Load 2 and 3 who do not hold any FTR see a decrease in their payoffs because of increased LMPs at their buses. The joint effect of contingency and demand variability on the payoffs of the participants is negligible. In short, contingency and demand variability have significant effects on the payoffs of the market participants. The direction of these effects change from bidder to bidder and from case to case showing the complex relations between the market dynamics such as equilibrium LMPs, whether the bidder holds any FTR, generation quantities.

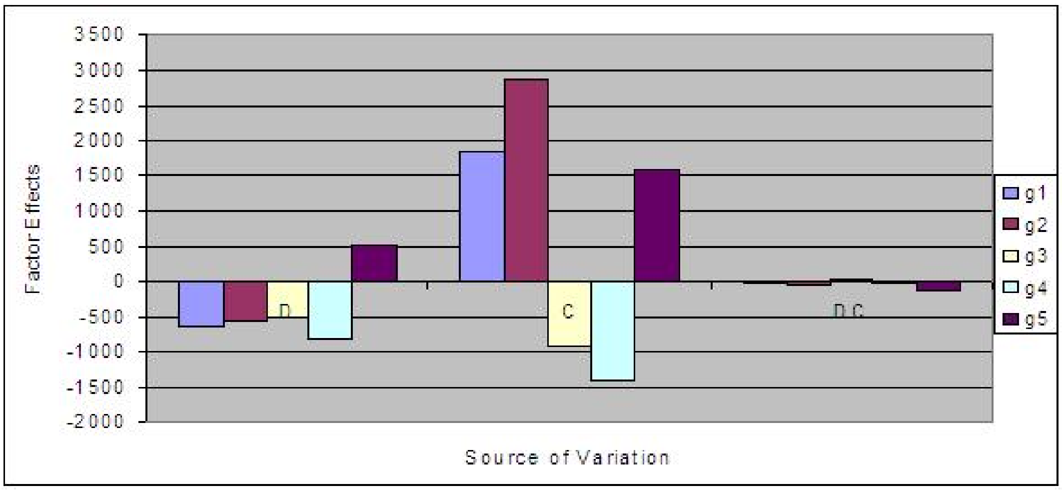

Figure 6.2 Generator Factor Effects for Contingency-Demand Variations

6.4 Impact of Generator Cost Function Variations

In order to analyze the effect of generator cost function variability on the market equilibrium payoffs, linear cost coefficient of generator 2 and 4 is varied at two levels (low and high) forming a 2^2 factorial design. These coefficient levels are shown in Table 6.8. Notations used in this table are as follows

1. Low marginal cost for generator 2 and low marginal cost for generator 5 ((1))
2. Low marginal cost for generator 2 and high marginal cost for generator 5 (g5)
3. High marginal cost for generator 2 and low marginal cost for generator 5 (g2)

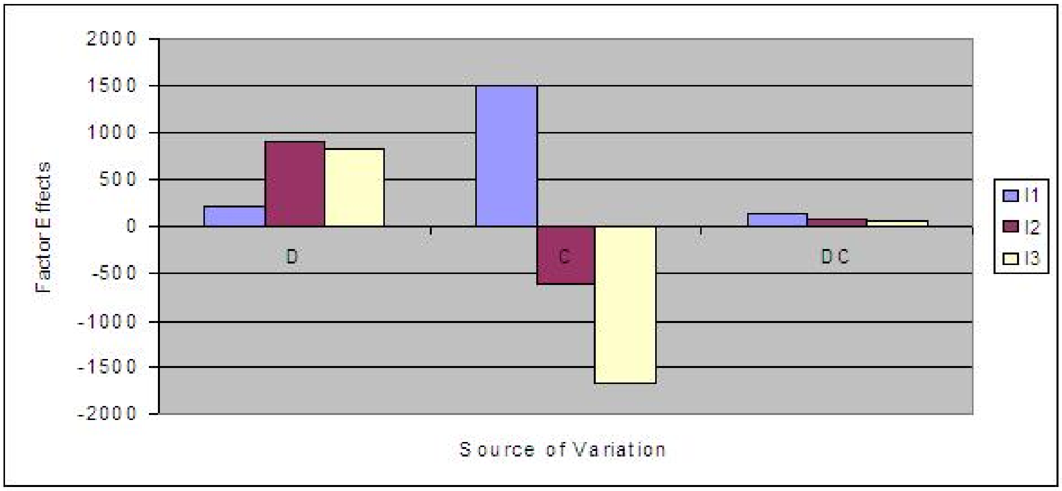

Figure 6.3 Load Factor Effects for Contingency-Demand Variations

Table 6.8 Equilibrium Payoffs for Different Cost Function of Generator 5 and 2

	Source of Variation			*Payoff ($)*							
	G5	G2	G5G2	g1	g2	g3	g4	g5	l1	l2	l3
(1)	-1	-1	1	-3541	-6118	3265	2752	4480	-16586	-14873	-14208
g5	1	-1	-1	2185	-164	6970	9885	5944	-23058	-25263	-23292
g2	-1	1	-1	-3666	-7879	3334	2759	4413	-16678	-14830	-13970
g5g2	1	1	1	2228	-1458	7061	9904	5969	-23108	-25318	-23340
	Factor Effects			*Cost Function Coefficients of Generator 2 and 5*							
g1	5810	-41	84								
g2	6187.5	-1527.5	233.5	*(1)*		*c1*	*c2*	*g5*		*c1*	*c2*
g3	3716	80	11		*g2*	14	0.014		*g2*	14	0.014
g4	7139	13	6		*g5*	20	0.025		*g5*	40	0.025
g5	1510	-21	46								
l1	-6451	-71	21	*g2*		*c1*	*c2*	*g5g2*		*c1*	*c2*
l2	-10439	-6	-49		*g2*	28	0.014		*g2*	28	0.014
l3	-9227	95	-143		*g5*	20	0.025		*g5*	40	0.025

4. High marginal cost for generator 2 and high marginal cost for generator 5 (g5g2)

5. Effect of generator 5 marginal cost function (G5)

6. Effect of generator 2 marginal cost function (G2)

7. Joint effect of generator 5 and 2 marginal cost functions (G5G2)

Four contingency and three demand scenarios presented in the previous section (see Table 6.5 and 6.6) stay same for this experimentation. A new joint contingency

Table 6.9 Joint Contingency-Demand Probability Matrix

	Demand Scenarios		
Contingency Scenarios	*1*	*2*	*3*
1	0.640	0.080	0.080
2	0.056	0.007	0.007
3	0.056	0.007	0.007
4	0.048	0.006	0.006

- demand probability matrix which is composed of medium contingency and demand variability, is generated for this problem (unlike the low - high contingency - demand variability combinations in the previous section). This new joint probability matrix is given in Table 6.9.

A bigger FTR market whose data are shown in Table 6.10, is created for this problem. As seen from the table, generators 1, 2, and 3, and loads 1 and 2 continue to be the competitors with the same FTR paths in the FTR market, however, generator 2 has an extra FTR path, $3-2$. The bidding parameters and factors of both linear and quadratic components of the benefit function are also given in Table 6.10. Obligation and option type FTRs are still part of FTR bidding strategy of the bidders. Generators' bidding parameters and factors for energy market settlement remain same as shown in Table 6.2.

Equilibrium payoffs and factor effects of the participants for the marginal cost function combinations are given in Table 6.8. The changes in the factor effects based on source of variations are presented in Figure 6.4 for generators and in Figure 6.5 for loads. When the bus LMPs are examined, it is seen that generator 5's bidding price affects the LMPs over the whole network (price setter) whereas generator 2's bidding price has a minimal affect over the bus LMPs including bus 1 where she

Table 6.10 FTR Market Data for Cost Function Variations Variations

Bidder	FTR Source Bus	FTR Destination Bus	Benefit Fun. Lin. Param.	Benefit Fun.Qua. Param.
g1	1	5	10	0.002
g2	1	2	10	0.002
	3	2	10	0.002
g3	3	4	10	0.002
l1	3	4	10	0.002
l2	3	5	10	0.002
	Linear Strategy		Quadratic Strategy	
	4	8	3	8

is located (price taker). This observation explains the trend in the figures. As seen from Figure 6.4, all generators' payoffs are higher when generator 5 has a higher marginal cost. A higher marginal cost for generator 5 makes her to bid higher in the energy market resulting in higher LMPs and increased energy profits for the generators. Higher LMPs mean increased energy costs for the loads as seen in 6.5. While the increase in the payoff of generator 4 is maximum, generator 5 has a lower increase in her payoff. It is observed that in this network generator 4 and 5 act like substitutes. Thus, when generator 5 bids higher price for power generation, ISO who has a goal of minimizing total cost of power generation, allocates more MW to be produced by generator 4 and less by generator 5 creating more profit for generator 4 and less for generator 5. Since generator 2 is price taker, the LMPs on the buses do not differ much when she bids higher price due to higher marginal cost. The only participant whose payoff is significantly affected by generator 2's higher price bidding is herself which is obviously because of her higher marginal cost. To summarize, impact of a generator's production cost function is a product of complex relations among the market dynamics. If a generator has a higher cost function, this may decrease her equilibrium payoff, may or may not affect the equilibrium payoffs of the other participants depending on whether she is a price maker or a price taker.

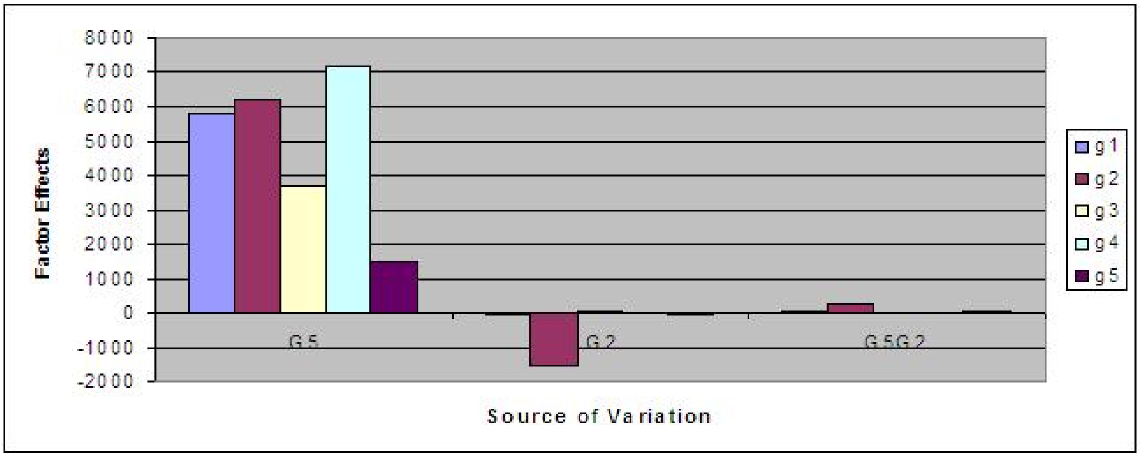

Figure 6.4 Generator Factor Effects for Generation Cost Variations

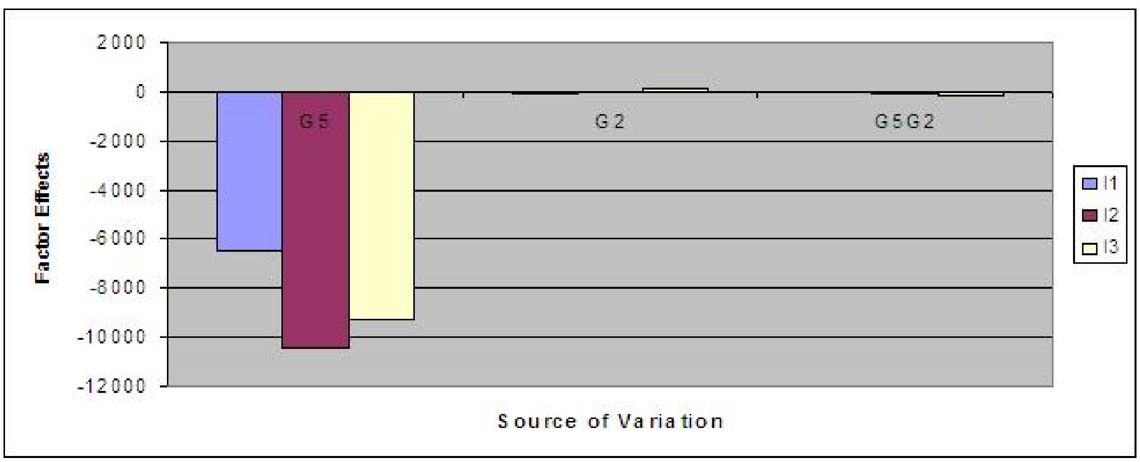

Figure 6.5 Load Factor Effects for Generation Cost Variations

CHAPTER 7

CONCLUSIONS

Financial transmission right is considered an important mechanism for power market participants to hedge against price uncertainties resulting from transmission congestion. FTR also serves as a means of generating revenue in a deregulated market, in a way similar to the stocks in the financial sector. A framework for FTR allocation was originally introduced in [10]. Though bidding strategies in an FTR market is highly influenced by the bidding strategies in the energy market and vice versa, to our knowledge, no attempt has been made prior to this research to jointly model and examine equilibrium bidding behaviors in FTR and energy markets.

In this dissertation, a game theoretic model for examining non-cooperative bidding strategies for acquiring FTRs in a deregulated power market is presented. The matrix game theoretic model presents a significant departure from the commonly used bi-level optimization approach found in the literature, and it allows consideration of multidimensional bids with many bidders, multiple FTR paths, different obligation and option prices, and contingencies and varying demands.A value iteration based RL algorithm is used as a solution tool for the matrix game model. A sample power network is used in elaborate demonstration of the matrix game model for analyzing FTR bidding strategies. Sixteen different numerical scenarios are constructed from the sample network for which equilibrium FTR bidding solutions are presented. The quality of the solutions in terms of their Nash property and bidder payoffs are discussed. It is shown that the value iteration based RL algorithm is able to find Nash equilibrium solution in majority (10 out of 13) of the problem scenarios for which pure strategy Nash equilibrium exist.

Additional experimentations were also conducted to study the impact of bid parameters on equilibrium solution. The numerical results show that price is an important factor and its value could significantly alter the FTR allocation outcome. The FTR quantity bid is shown to be a function of risk and variance parameters of the network. Without high values of risk and variance, quantity bid could behave in a nonstrategic manner (higher the better). The combination of obligation and option (type mix bid) may have significant impact on the payoffs of the bidders, and hence should be considered while bidding.

A statistically designed 2-level factorial experiment provided an ideal means for investigating impacts of four different network related parameters (contingency, ΔLMP, variance of ΔLMP estimates, and risk coefficient of the bidders) on the equilibrium outcome. The results show that all four of the factors significantly impact equilibrium FTR settlement, but their interactions were not significant. It was found that some contingencies in the network can create favorable bidding positions for some of the bidders. The results indicate that an accurate consideration of the network parameters is crucial in determining an equilibrium bidding strategy.

In the joint FTR and energy market model,LMPs are directly attained from the energy market where generators compete to maximize their payoffs. Integration of FTR and energy markets reveals the complex relations among the market dynamics. It also allows to incorporate detail characteristics of power market such as varying contingency and demand scenarios. Generators consider all contingency and demand scenarios and try to maximize their expected payoffs. Experimentations with the joint FTR and energy markets via a PJM-5 bus network example showed that FTR holdings have a significant impact on both the energy market strategies and the joint equilibrium payoffs. When the contingency and demand scenario variabilities were changed, payoffs of the participants were affected. Marginal cost functions of the generators were also found to have influence on the equilibrium market settlement. It has been observed that depending on the production capacity and network location, some generators have influence over all network LMPs (price setters) while others do not (price takers).

The model and the solution approach presented here will help the market participants to better evaluate their FTR and energy bidding strategies, and thus aid the markets to reach an equilibrium, reducing uncertainty for the participants. The research outcomes will also serve as valuable tools for the designers of the restructured power markets. It is also expected that restructured markets designed using the approach developed here will provide a higher level of market reliability than what has been experimented so far.

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